

ENERGY INDEX DECOMPOSITION
METHODOLOGY AT THE PLANT LEVEL

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CHAPTER I

INTRODUCTION

Motivation of Study

The motivation for this research is to develop a methodology for an economically based energy performance monitoring system that incorporates production information. This performance measure will closely monitor energy usage and reflect the production efficiency as a part of an ongoing process, a facility manager can keep track and in the future, predict on when to perform a recommissioning process.

Recommissioning is a thorough and detailed process of reassuring that the facility mechanical and electrical systems (production and production support equipment) are operating optimally according to the building's design intent. There is currently no definite schedule on when the recommissioning needs to be perform, Turner [2005] provided guidelines that the facility should consider recommissioning when one or more of the following occurs ("triggers")

1. High energy consumption,
2. Occupant complaints,
3. Maintenance staff complaints (problems),
4. Economic interests (lessen operating costs including energy and maintenance),
5. New systems or significant expansion of existing system.

Since most commercial building energy consumption is from environmental control systems (i.e., HVAC) and the function of the building is relatively constant compared to

manufacturing facilities, measuring these “triggers” is doable and relatively straightforward. For example, several studies by Liu and Claridge [2003] used energy system sub-metering as the main part of an ongoing commissioning process to continuously optimize a commercial building. A similar process of energy utilization monitoring as a tool to trigger recommissioning has not documented for an industrial facilities. This is likely due to the wide variations in product mix, product types, weather changes, production level, process changes, etc.

One of the popular methods used in energy performance measurement is index numbers. There has been considerable research on energy performance indexes utilizing energy intensity indicators to monitor changes in production efficiency. The idea was originated by an economist in the early 1900s, Dr. Irving Fisher [Barber 1996]. However, most of the research work focuses on large scale indicators (national economy) as opposed to small scale indicators (individual company). Energy intensity indexes are used to compare and track changes in energy intensity at the national and end-use sector levels.

There has been active research work on energy intensity indicators and energy intensity indexes on large scale economy i.e., country level, sector level, and industry level. Recent research direction focuses on the development of energy intensity indexes which incorporate environmental impacts [Ang 2000] and the national or sector levels. A small number of researchers have also been investigating the use of energy intensity indicators at the facility level (plant level). These researchers focus on comparisons of energy intensity between similar manufacturing plants in order to establish benchmarks in energy usage for general plants, best practice plants, and low efficiency manufacturing plants [Worrell 2003]. Recently, energy efficiency monitoring over time with the energy intensity index has also been used in the environmental conservation area and at the national level [Bernard 2005]. The lowest monitoring system in this area was at the sector level.

Energy intensity indicators and energy intensity indexes are useful tools that paint a picture of the status of a country's, industry's, or sector's energy efficiency. This enables

researchers, economists, and policy makers to establish benchmarks between countries, industries, or sectors and establish energy policy accordingly

The goal of this research is to develop a practical energy performance monitoring index for use at the plant level to monitor the facility's energy efficiency usage over time which will help the facility justify when to reevaluate the plant's overall energy efficiency through recommissioning. A contribution of this research is to incorporate the potential savings to be generated by including the production into the indexes. It is an extension of two recent research topics, energy intensity studies and energy intensity index studies.

CHAPTER II

LITERATURE REVIEW

Introduction

There has been considerable research on monitoring energy usage in industry. However, most research has focused on high level usage (i.e., continent, country, sector, or industry). Since the early 1990s, researchers directed their work to develop more sophisticated energy monitoring decomposition methodologies. Examples include Liu and Ang [1992], and Ang [1994] who monitor energy usage at lower levels but stopped at the industry level. Beginning in the late 1990s and continued through the early 2000s, research directions have changed to incorporate environmental factors into the index decomposition methods at the industry level [Bernard 2005].

This chapter introduces the fundamental components and types of energy monitoring index decomposition methodologies which include energy intensity, decomposition methodologies, and energy monitoring index and research work in these areas to date.

2.1 Energy Intensity

Energy intensity (EI) is a measure of the efficiency with which energy resources are being used to produce goods [Freeman 1997]. EI is commonly expressed as ratio of energy input (e.g., Btu, kWh) to useful output (e.g., tons of products, dollars of revenue).

Energy intensity is also referred to in some publications as energy efficiency indicators (EEI) [Phylipsen et al.1998]. In this research, the term EI will be used to identify these measures. EIs are divided into two categories, physical EIs and economic EIs. Physical EI is based on the physical amount of energy used in the process. The energy input is expressed in thermodynamic units (e.g., Btu of delivered energy consumed in the production of aluminum) and useful output measured in volume of output e.g. tons of aluminum or market value of output e.g. dollars of aluminum. The economic EI is different from the physical counterpart because it expresses the energy input in terms of monetary value. There are several ways to measure energy input and production output. These are reviewed in the following two sub-sections.

2.1.1 Measures of Energy Input

Freeman [1997] stated that three measures of energy consumption are site consumption of energy, total inputs of energy, and offsite produced energy. These are explained more completely below.

1. Site Consumption of Energy

Site consumption of energy is the most comprehensive measure of energy consumption and represents the first use of energy sources regardless of whether they are consumed as a fuel or as a non fuel (raw material). This measure does not include byproduct fuels produced onsite from previously counted energy inputs.

2. Total Inputs of Energy

Total input of energy includes all energy sources used to produce heat and power and to generate electricity whether produced offsite or onsite. This metric excludes energy generated from the facilities own raw materials (e.g., calcined carbon process).

3. Offsite Produced Energy

Offsite produced energy includes all energy sources purchased or transferred from offsite to produce heat and power and to generate electricity. All non fuel uses of energy and all byproduct energy are excluded.

2.1.2 Measures of output

Similar to the energy input, measures of output can be divided into two types, volume based output and value based output. Volume based output is the most straightforward measurement for each facility. However, it does not reflect the bottom line or profit of the company because it does not have a monetary value tagged to it. Table I shows an example of the Department of Energy's measures of output by volume [Freeman 1997].

TABLE I
INDUSTRIES OUTPUT DATA MEASURES¹

Demand Indicators	
Industry	Volume-based
Aluminum	Aluminum production (tons)
Cement	Cement production (tons)
Chlor-alkali	Chlorine and sodium hydroxide production (tons)
Copper	Promary copper production (tons)
Corn wet milling	High fructose corn syrup (tons)
Lime	Lime production (tons)
Lumber	Lumber production (board-feet)
Nitrogen fertilizers	Nitrogen fertilizer material production (tons)
Paper	Paper production (tons)
Paper board	Paper board production (tons)
Plywood	Plywood production (square feet 3/8" basis)
Pulp	Pulp production (tons)
Steel	Raw steel production (tons)
Petroleum	Petroleum products (barrels)

In order to better associate the economic values to the measures of output, alternative measures of output have been proposed. Some of these measures are reviewed below.

1. Gross output (Q)

Gross output is a physical volume of output (e.g. tons of steel) and the most comprehensive measure of manufacturing production. It includes sales and inventory (I) change [Phylipsen 1998].

¹ Adapted from Table 1 in Freeman [1997]

2. Value of shipments (VS)

Value of shipment is a measure of economic activity expressed in constant dollars. VS can be calculated from current dollar value of shipments (quantity produced multiplied by current sales price) adjusted for inflation by a price index. This measure reduces the impact of inflation when comparing shipments over time.

$$VS = (VS^c)/P \quad (\text{Eq. 1})$$

Where

VS = Value of shipment,

VS^c = Value of shipment in current dollars (\$ at the time of sale),

P = Price index.

3. Value of production (VP)

Value of production is measured in constant dollars composed of value of shipments and net additions to inventories (I) then adjust for inflation with price index (P).

$$\begin{aligned} VP &= (VS^c + I^c)/P \\ &= VS + I \\ &= (Q)(P^c)/P \end{aligned} \quad (\text{Eq. 2})$$

Where

VS = Value of shipment,

VS^c = Value of shipment in current dollars (\$ at the time of sale),

Q = Gross output,

I^c = Value of inventory in current dollars (\$ at the time of sale),

I = Value of inventory at time of addition,

P = Price index,

P^c = Price in current dollars.

If changes in the price index P correctly reflect the changes in current dollar prices, then VP and Q will move together over time [Freeman 1997].

4. Value added (VA)

Value added is measured in constant dollars. It is the value of shipments less the cost of materials (CM), and adjusted for inflation.

$$\begin{aligned} VA &= (VS^c - CM^c) / P \\ &= VS - CM \end{aligned} \quad (\text{Eq. 3})$$

Where

VS = Value of shipment

VS^c = Value of shipment in current dollars (\$ at the time of sale)

CM = Cost of materials

CM^c = Cost of materials in current dollars (\$ at the time of sale)

P = Price index

Having considered measures of input and measures of output, we return now to our more general discussion of energy intensity

As shown in Table II, the US Department of Energy lists the various potential indicators of energy intensity in the manufacturing sector. Choices of which indicator of energy intensity to use vary based on the researcher's preference and situation.

TABLE II
ENERGY-INTENSITY INDICATORS FOR THE MANUFACTURING SECTOR

(Thousand Btu/1987 Dollar)
Energy / Gross Output
Energy / Industrial Production
Energy / Value Added
Energy / Gross Product Originating
Energy / Value of Shipments
Energy / Value of Production
Energy / Adjusted-Capacity Value of Production

Recent studies by Worrell [2003] and Boyd [1997] incorporate productivity effects into the energy intensity measures to justify the benefit of investing in energy efficiency improvement measures. Both papers conclude that implementing energy management best practices in the iron and steel industries increase overall productivity of the industry.

Three major studies done the between 1982 and 1994 at the plant level are most closely related to this dissertation are Turner and Parker [1982], Boyd, et al. [1992], and Boyd, et al. [1994].

Turner and Parker [1982] introduced the concept of energy accounting used as energy productivity monitoring and control measurement systems. The study uses a “one-shot” energy efficiency measures composed of energy per unit of production (Btu/unit), energy per heating or cooling degrees (Btu/degreedays), and energy per facility area (Btu/square foot) as indicators. The research used the monthly indicators to compare two or more periods of the same months, for example, February energy indicators in the past 3 years. Turner and Parker [1982] also introduced the Carborundum Accounting System where product mix effect and degree-day based heating and cooling effect are used to adjust the indicators.

The first was completed by Boyd, et al. [1992] on modeling plant-level industrial energy demand with the manufacturing energy consumption survey (MECS). The research is a survey and Phase I of a project to help the DOE determine the applicability of the Manufacturing Energy Consumption Survey (MECS) database and the Longitudinal Research Database (LRD) for industrial modeling and analysis. The paper focuses on six industries, paper mills, alkalies and chlorine, nitrogenous fertilizers, cement hydraulic, blast furnaces and steel mills, and primary aluminum. The report also describes several measures used at the plant level, namely energy intensity and technical efficiency. The results showed that the technical efficiency and distribution of energy intensities vary significantly at the plant level. Energy prices also vary significantly at the plant level where higher energy consumption plants pay less per unit energy (i.e., dollars/kilowatt hours).

The second study by Boyd, et al. [1994] examined the vintage-level energy and environmental performance of manufacturing establishments. The report examines relationships between an industrial plant's vintage and its energy and environmental performance. It first examines new plants in the six major energy intensive industries. The report then focuses on the steel and cement industries. The purpose of the study was to;

1. define vintage and its metrics,
2. examine the energy intensities and pollution-abatement costs at plant level for different vintages,
3. determine the affect of manufacturing industry's vintage distribution.

The Vintage was assigned on the basis of external data, and a series of analyses which involve, energy intensity, utilization of each vintage, and the share of capacity or capital stock

The study also defined energy and environmental performance which incorporated the Total Factor Productivity (TFP) approach and production model approach which used the following models;

1. smooth factor substitution models,
2. Putty-Clay models,
3. Fixed-Coefficient models.

The models above are mentioned as additional information but are not relevant to this research and therefore not presented in detail.

The production efficiency used by Boyd, et. al. [1994] incorporated five input measures including capital, labor, electricity, fuels, materials, and output.

The study also defined energy intensity as;

1. Input/output ratio,
2. Energy/capacity ratio,
3. Energy/ capital stock ratio,
4. Energy/output tonnage ratio.

The results of the study show that newer plants (later vintage) exhibit lower fossil fuel intensities. The most significant declines were in the steel and cement industries.

2.2 Index Numbers

Index numbers are statistical averages in time series that show how values compare by using ratios of items selected as representative of all items of a class of economic data. Index numbers are usually designed to equal 100 for a base period and changes in their components are computed at regular intervals in an attempt to indicate general changes in a specific class of economic data [Greaves and Coleman 1999].

Index numbers of price show the average percentage change of prices from one point in time to another. The percentage change in the price of a single commodity from one time to another can be calculated by dividing its price at the second time by its price at the first time. The ratio between these two prices is called the relative price of that particular commodity in relation to the two times. In the same manner, the index number can be

used to calculate percentage change in wages, quantity of goods imported or exported, or any subject matter involving divergent changes of a group of magnitudes. The index numbers are expressed in terms of time and can be applied to compare two magnitudes of a group of elements under any one set of circumstances and their magnitudes under another set of circumstances [Fisher 1927].

Energy index analysis is a study of changes in energy efficiency indicators through time. Early researchers chose to decompose industrial energy demand by using the Divisia approach. This includes the decomposition of the aggregate energy intensity index measured in terms of energy consumption per unit output of each energy intensive industry [Ang 1995]. Later research identified and discussed the issues and problems that commonly occur in constructing energy indicators; especially due to alternative measures of output in intensity indicators [Freeman 1997]. There are currently three energy intensity indexes commonly used, Laspeyres index, Divisia index, and Fisher Ideal index. Recent research focus is at the country level down to sector level (industry level). The direction of the energy intensity index analysis points toward environmental impacts, especially green house gas. The following is an overview of the development of each of these energy intensity indexes.

Laspeyres index

The Laspeyres index was proposed in 1871 by a German economist Étienne Laspeyres [Wikipedia 2006]. The index was proposed for measuring current prices or quantities in relation to those of a selected base period. It is a statistical price index which is calculated from a set ("basket") of fixed quantities of a finite list of goods by assuming that we know the prices at two different points in time. The analysis proceeds as follows.

Let the price index be one in period 0 (reference period), which is then the base period. Then the value of the index in the first period (period 1) is equal to this ratio: the total price of the basket of goods in period two divided by the total price of exactly the same basket in period one. As for any price index, if all prices rise the index rises, and if all prices fall the index falls [Britannica 2005]. The index

shows the change in cost of buying in the current period, 1, the same basket of goods as in the base period, 0. The index measures the effect of price changes when the base period consumption levels are hypothetically maintained. This assumption expresses the weakness of the index [Selvanathan and Rao, 1997]. If the reference quantities (R) are selected as the base period quantity, i.e., $q_{R1} = q_{01}$, $q_{R2} = q_{02}$, $q_{R3} = q_{03}, \dots, q_{Rn} = q_{0n}$ then

$$L_{01} = \frac{\sum_{i=1}^n p_{i1} q_{i0}}{\sum_{i=1}^n p_{i0} q_{i0}} \quad (\text{Eq. 4})$$

Where

p_{i1} = The cost of buying the i^{th} good in period 1

p_{i0} = The cost of buying the i^{th} good in period 0

q_{i0} = The quantity of i^{th} good bought in period 0

L_{01} = Laspeyres index of time 0 and t

This index has been one of the most popular indexes used in energy decomposition methods studies, having been used by Alcantara and Roca [1995], Ang [1987-1999], Chen and Wu [1995], Boyd et al. [1987], and Howarth et al. [1993].

Divisia Index

The Divisia index approach was introduced by Boyd [1987] by using the Tornqvist approximation stated as reference, detail of Tornqvist approximation is not relevant to this research. The Divisia index approach has been widely used in governmental statistics of energy intensity determination at the country, sector, and sub-sector levels. The Divisia index approach allows a decomposition of the percentage change in energy use into separate changes in total activity, economic structure, and energy intensity at the component level. When applied to annual data, the decomposition is performed for changes from one year to the next. The resulting changes are cumulated to a time series index that is normalized to one in

a selected base year. The chain-weighted nature of the index makes the choice of base year arbitrary from the standpoint of the percentage changes over time. Divisia indexes assume that the data on the various factors vary in more or less a continuous fashion. Liu et al. [1998] indicate that the data are assumed to be available at every moment of time, instead of only at discrete (annual, quarterly, etc.) points in time [EIA 2005]. The index has many desirable properties that are useful for decomposition analysis including variable weighting over time and additive decomposition of relative growth rates [Liu et al. 1998]. The detail of Divisia index will be described in detail in Chapter 4.

Paasche index

In contrast to the Laspeyres index, the Paasche index measures the effect of price changes from period 0 to 1 if current period consumption had been used in the base period. The index was proposed by Paasche [1874]. If the reference quantity is selected as current period quantity vector, i.e., $q_{01}=q_{R1}$, $q_{02}=q_{R2}$, $q_{03}=q_{R3}, \dots, q_{0n}=q_{Rn}$, then

$$P_{01} = \frac{\sum_{i=1}^n p_{i1} q_{i1}}{\sum_{i=1}^n p_{i0} q_{i1}} \quad (\text{Eq. 5})$$

Where

- p_{i1} = The cost of buying the i^{th} good in period 1
- p_{i0} = The cost of buying the i^{th} good in period 0
- q_{i1} = The quantity of i^{th} good bought in period 1
- I_{01} = The index of price change between period 0 and 1
- P_{01} = Paasche index of time 0 and t

Fisher Ideal Index

The Fisher Ideal Index is the most recent introduction by Boyd [2004]. The index uses the chain weighted Fisher Ideal Index to resolve the residual problem in prior

indices. Residual problem is discussed in Chapter 4. This index is the geometric average of the Laspeyres and Paasche indices.

$$I_F = \sqrt{I_L \cdot I_P} \quad (\text{Eq. 6})$$

Where I_F = Fisher Ideal index
 I_L = Laspeyres index
 I_P = Paasche index

Index numbers are statistical averages in time series that show how values compare by using ratios. The result is the percent changes between the period of interest and the reference period. This characteristic of index numbers can be applied to energy efficiency monitoring shown in later sections of this research.

2.3 Aggregation Levels

Energy decomposition methodology is a process of breaking down an entity's energy usage in order to study the sources of process energy consumption and its characteristics.

Energy consumption can be determined on various levels as shown in Figure 1

1. The nation level is an aggregated level of several sectors.
2. The level of main sectors (e.g., manufacturing industry, residential, services, transportation)
3. The level of sectors (e.g., food and drugs industry, basic metal industry)
4. Level of individual firms
5. The level of processes within subsectors or of the individual firms

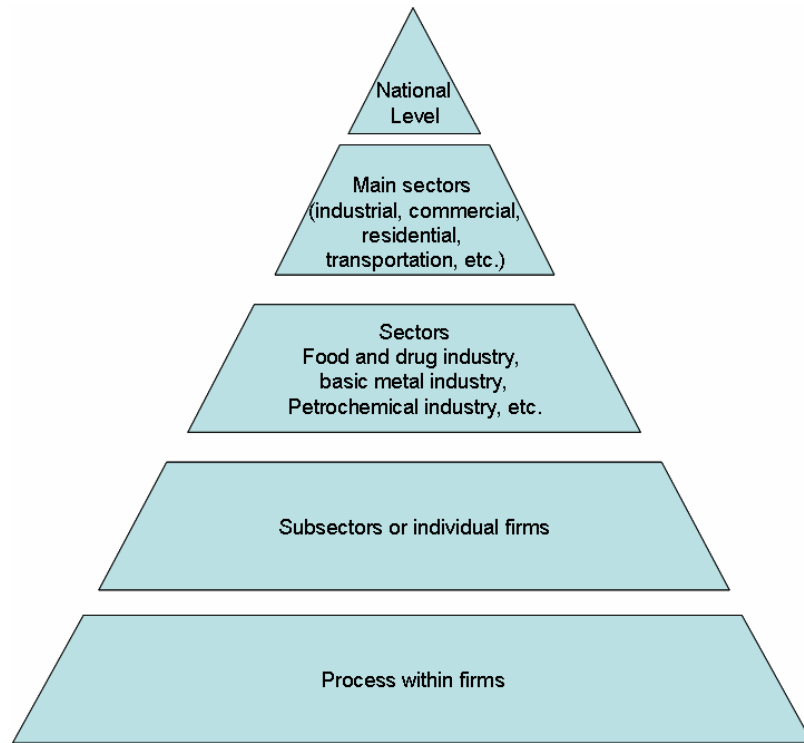


Figure 1 The energy indicator pyramid (with sources of data)²

Economic energy indicators can be developed on each level. They are generally developed in a way that depicts changes in overall energy consumption that are decomposed into changes in activity level.

There have been significant studies of economic efficiency indicators at the country, industry, and sector level by using macro economic indicators and indexes since the early 1980's [Ang1995]. Reitler et al. [1987] analyzed the factors influencing energy consumption in industry. Reitler et al. [1987] introduced a method to determine the role of changes in energy consumption in fuel and electricity in relation to the effects on production structure and specific consumption. They also used the Specific Energy Consumption (SEC) which is a ratio between energy consumption and an index of industrial production in that period. However, since the indicators were developed, there has been no evidence that these indicators were used to develop energy efficiency indexes at the plant level by either the decomposition method down to the process level

² Adapted from International Energy Agency, "Indicators of Energy Use and Efficiency: Understanding the link between energy and human activity", OECD Publications, Paris 1997

or aggregation method from the process up to the plant level (see Figure 1 on previous page).

There are several energy indicators and each is used to measure different aspect of the energy usage. A recent study by Bernard [2005] showed that there have been efforts to compile these measurements and assess the information by using a principal component analysis to assess the information derived from several energy indicators. However, due to the large number of variations, it was difficult to establish meaningful benchmarks that could be used.

A study by Brown et al. [1996] on the hierarchical structure of manufacturing systems provided a preliminary assessment of the quantity and quality of waste energy that may be economically practical to recover in the industrial sector. The report covered energy utilization data for 60 four-digit SIC (standard industrial code) industries which represent 70% of the United States industrial manufacturing energy consumption. The report documented general flow diagrams and heat and mass balance for each operation. The energy and mass balances were on a per unit basis for a each unit operation for individual industrial processes. The report also presented process temperature, pressure, fuel requirements, thermal efficiency, and radiation and convection losses for each operation.

By linking this research and utilizing the process levels presented and the plant level study by Boyd [1994], a plant level index could be created by incorporating relevant information tracked over time. By applying the index number methodology, a measure can be created to represent a short interval of time and represent the plant's overall effectiveness from an energy and environmental standpoint (but in a financially driven nature).

According to Phylipsen [1998]'s methodology, energy efficiency indicators are developed by the following steps:

1. Create process routes and system boundaries,
2. Develop an energy efficiency indicator pyramid for the facility,
3. Determine the data required by looking at the disaggregated levels and find potential sources which may include,
 - 3.1 Gross output,
 - 3.2 Value of shipments,
 - 3.3 Value of production,
 - 3.4 Value added,
 - 3.5 Production index.
4. Perform energy efficiency analysis by calculating the Specific Energy Consumption (SEC) and other components to obtain the Economic Energy Efficiency Indicator.

2.4 Decomposition Methodology

In general, the decomposition methodology is a process of modeling time series that exhibit trend and seasonal effects. The basic idea behind these models is to decompose the time series into several factors i.e., trend, seasonal, cyclical, and error [Bowerman and O'Connell 1987]. Decomposition of industrial energy consumption is a process of decomposing the indexes in order to study the energy impacts of structural change and energy efficiency improvements. There are two major decomposition methods commonly used to study industrial energy consumption, multiplicative decomposition and additive decomposition.

2.4.1 Multiplicative Decomposition

The multiplicative decomposition method models the time series by computing or calculating the factors in a multiplicative form. This model is useful when modeling time series that display increasing or decreasing seasonal variation. Equation 7 depicts the general multiplicative decomposition model defined by Bowerman and O'Connell [1987]

$$y_t = TR_t \cdot SN_t \cdot CL_t \cdot IR_t \quad (\text{Eq. 7})$$

where

y_t = The observed value of the time series in time period t ,

TR_t = The trend component (or factor) in time period t ,

SN_t = The seasonal component (or factor) in time period t ,

CL_t = The cyclical component (or factor) in time period t ,

IR_t = The irregular component (or factor) in time period t .

2.4.2 Additive Decomposition

The additive decomposition method models the time series by computing or calculating the factors in an additive form. This model is useful when modeling time series that display constant seasonal variation. Equation 8 depicts the general additive decomposition model defined by Bowerman and O'Connell [1987]

$$y_t = TR_t + SN_t + CL_t + IR_t \quad (\text{Eq. 8})$$

where

y_t = The observed value of the time series in time period t ,

TR_t = The trend component (or factor) in time period t ,

SN_t = The seasonal component (or factor) in time period t ,

CL_t = The cyclical component (or factor) in time period t ,

IR_t = The irregular component (or factor) in time period t .

2.5 Energy Index Decomposition methodology

The index decomposition methodology was introduced during the 1970s and was used to study the changes in product mix in industrial energy demand [Bossanyi 1979 and Nakamura 1978]. Ang and Zhang [2000] described the index decomposition methodology as a technique that provides a linkage between an aggregate and the original raw data gathered from industries where the information of interest (production quantities, energy consumption, emission, etc.) is captured in a concise and usable form. The notion is similar to the economic index numbers used to study the price and quantity level changes in aggregate commodity consumption. This methodology is also referred to as index number decomposition analysis by Rose and Casler [1996]. From the previous section we learned that there are many indexes used in the index decomposition methodology. In recent research (1992 to 1999) the indexes commonly used are Laspeyres (45%) and Divisia (28%) [Ang 2000]. This research considers these two commonly used indexes.

Index decomposition methodology can be classified into two major approaches, the energy consumption approach and the energy intensity approach. A general framework from Ang [1994] is shown in Figure 2 on the next page. The energy consumption approach uses the decomposition technique to study changes in overall (total) industrial energy consumption over a period of time. The technique incorporates changes in aggregate production (production effect), production structure (structural effect) and sectoral energy intensities (intensity effect). The energy intensity approach methodology uses the decomposition method on the changes in the aggregate energy intensity (not the total consumption) and can be divided into several methods.

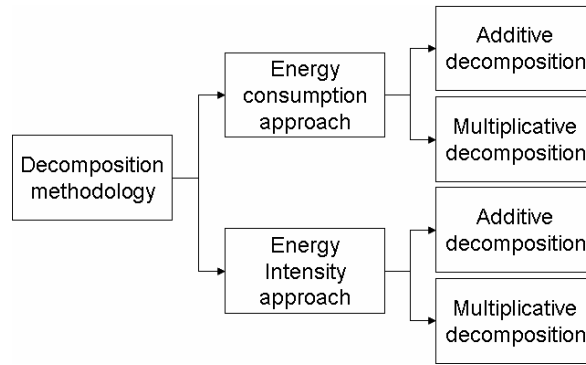


Figure 2 General framework of the index decomposition methodologies³

This research uses these common index decomposition methods and extends them to the plant level. Ang and Zhang [2000] concluded that in the last decade, the Laspeyres and the arithmetic mean Divisia index methods have been the two most often used decomposition methods. This research will use this argument to focus on these two index methods.

2.5.1 Aggregate Energy Consumption Approach

The Aggregate Energy Consumption approach was used by Liu et al. [1992] who studied the Divisia index in detail. They also proposed a new method based on this index called the Adaptive Weighting Divisia method. The paper's emphasis was on the methodological aspect of decomposition. However, the results of a study using the data of Singapore were shown to illustrate the application and the associated statistical problems of other existing methods. The use of the Divisia index in the decomposition of changes in industrial energy use was first introduced by Boyd et al. [1987 and 1988] but they did not discuss the integral path problem. The research by Liu et al. [1992] expanded the 1980's research where the decomposition is based on a finite number of industrial sectors. The study was mentioned by Ang and Lee [1994] who summarized the five main energy consumption approaches including Laspeyres/Paasche Method, Marshall-Edgeworth Method, Simple Average Divisia Method, Parametric Divisia

³ Adapted from Ang [1994]

method, and Adaptive Weighting Divisia method. These methods are mentioned as an example, they do not pertain to this research.

2.5.2 Aggregate Energy Intensity Approach

Aggregate energy intensity is the ratio of total industrial energy consumption to industrial output. The energy intensity approach is the decomposition of changes in the energy intensity into contributions from structural and intensity effects. The energy intensity approach has been used in a large number of empirical and country specific studies. Examples of such studies are Bossanyi [1979], Jenne and Cattell[1983], Ang [1987], Li et al. [1990], Gardner [1993] and Huang [1993]. While Liu et al. [1992] and Ang and Lee [1994] have studied the general methodological and application issues related to the energy consumption approach, similar studies for the energy intensity approach were not reported until Ang [1994].

Based on the energy intensity approach, two parametric Divisia methods were introduced by Ang [1994] as parallel methods to the energy consumption approach by Liu et al. [1992] with the formulations in both multiplicative and additive forms. Ang [1994] then consider the five specific methods that are equivalent to those considered in Ang and Lee [1994]. Comparisons were also made between the energy intensity approach and the energy consumption approach in actual application. Empirical results obtained using time series data for Singapore and Taiwan were presented to illustrate the issues raised.

Ang [1994] introduced two general parametric Divisia methods based on the energy intensity approach, which are equivalent to those given in Liu et al. [1992] and describe their formulation in the multiplicative and additive forms. Ang [1994] then considered the five specific methods which are equivalent to those considered in Ang and Lee [1994].

The parametric Divisia index method allows a decomposition of the percentage change in energy use into separate changes in total activity, economic structure, and energy intensity at the component level. When applied to annual data, the decomposition is

performed for changes from one year to the next. The resulting changes are cumulated to a time series index that is normalized to one in a selected base year; this is referred to as the chain-weighted nature of the index which makes the choice of base year subjective from the standpoint of the percentage changes over time.

The Divisia indexes assume that the data on the various factors vary in more or less a continuous fashion. Liu et al. [1998] formally indicated that the data are assumed to be available at every moment of time, instead of only at discrete (annual, quarterly, etc.) points in time.

Liu et al. [1998] indicated that the Divisia index has many desirable properties that are useful for decomposition analysis. These properties include variable weighting over time and additive decomposition of relative growth rates. However, decomposition based upon a general Divisia index approach does not yield a unique set of results because one can develop an infinite number of indexes, each corresponding to assumptions as to how the factors change between the observed discrete points in time.

2.5.3 Selection of approach (Energy intensity or consumption)

Ang [1995] described the differences between intensity and consumption as the result of presentation and interpretation. In time series analysis, the energy intensity approach has the advantage of simplicity of results presentation because its estimated effects are typically expressed in indexes. Alternatively, particularly in periodwise decomposition, the results given by the additive energy consumption approach can be easily understood by non-specialists because the results are expressed in energy units.

The energy consumption approach is being not as appropriate as the energy intensity approach when studying the impact of structural change. In energy demand projection, an approach called energy elasticity approach is useful when elasticity estimates are needed to extrapolate future energy demand trends. When studying the energy consumption approach and the energy intensity approach, Ang [1995] suggested that the differences

between multiplicative and additive forms are minor. However, in the case of the energy elasticity approach, the multiplicative technique is superior to the additive forms.

2.5.4 Selection of method

Similar to general index decomposition methodology described in the prior section, the index decomposition methodology in energy consumption can be divided into multiplicative and additive index decomposition methodologies (Figure 2 Page 20). The decomposed factors are structural effect and efficiency effect as shown in equations 9 and 10.

$$D_{\text{tot}} = D_{\text{str}} \cdot D_{\text{int}} \quad (\text{Eq. 9})$$

$$I_{\text{tot}} = I_{\text{str}} + I_{\text{int}} \quad (\text{Eq. 10})$$

where

D_{tot} = Total change in overall energy usage (activity index) in time period t from multiplicative decomposition methodology,

D_{str} = Impact from structural change in time period t from multiplicative decomposition methodology,

D_{int} = Impact from energy intensity change in time period t from multiplicative decomposition methodology,

I_{tot} = Total change in overall energy usage (activity index) in time period t from additive decomposition methodology,

I_{str} = Impact from structural change in time period t from additive decomposition methodology,

I_{int} = Impact from energy intensity change in time period t from additive decomposition methodology.

The activity index (I_{tot}) shows the changes in the level of activity for a sector of the economy. The units used to measure activity differ by sector (e.g., square footage of floor space, industrial production measured in dollars, passenger-miles). Energy intensity indexes represent the effect of changing energy intensity for sub-sectors or detailed components of the economy. The structural index shows the effect of changing economic structure. This index is employed at higher levels of the indicators hierarchy and reflects

the impact on energy use of changes in the relative importance of sectors at lower levels of the hierarchy. It primarily shows the impact of shifts in the composition of sectors or sub-sectors with different absolute energy intensities. Since this research focuses on the plant level, the structural index refers to the percentage of product which is produced during a period i.e., changes in product mix.

By following the procedures from Lermitt and Jollands [2001] and Lui et al. [1998] via EIA [2005] we can demonstrate the index decomposition methodology. Consider the rate of change of total energy used for a particular sector of the economy where total energy (E) is expressed as the sum of the energy use for each of the components or sub-sectors within that sector. Typically, the component intensity is defined in terms of the available data as E_i/A_i . Thus, energy use for each component i can be represented as the product of activity (A_i) and the energy intensity in component i (I_i). Formally, we have

$$E = \sum_i E_i = \sum_i A_i I_i \quad (\text{Eq. 11})$$

where

- A_i = Product of activity for component i ,
- I_i = Energy intensity for component i ,
- E_i = Energy use to produce component i ,
- E = Total energy usage.

Assume that the activities for each of the components are measured in similar units (e.g., dollars, passenger-miles). Thus, total sector activity A is the sum of the activity levels for the components. If we express the share of the total sector's activity for component i (A_i/A) as S_i , Equation 11 can be rewritten as:

$$E = \sum_i A S_i I_i \quad (\text{Eq. 12})$$

where

- A = Total sector activity,
- I_i = Energy intensity for component i ,
- S_i = Share of total sector's activity for component i ,
- E = Total energy usage.

The derivative of equation 12 with respect to time is

$$\frac{dE}{dt} = \left(\sum_i S_i I_i \frac{dA}{dt} + \sum_i A I_i \frac{dS_i}{dt} + \sum_i A S_i \frac{dI_i}{dt} \right) \quad (\text{Eq. 13})$$

If we divide both sides of equation 13 by E, and perform the same manipulation to each of the terms on the right side, the entire expression can be recast in terms of logarithms or percentage growth rates of each of the variables

$$\frac{1}{E} \frac{dE}{dt} = \frac{d \ln E}{dt} = \frac{1}{E} \left(\sum_i A S_i I_i \frac{d \ln A}{dt} + \sum_i A S_i I_i \frac{d \ln S_i}{dt} + \sum_i A S_i I_i \frac{d \ln I_i}{dt} \right) \quad (\text{Eq. 14})$$

$$\text{Because} \quad \frac{A S_i I_i}{E} = \frac{E_i}{E} = w_i \quad (\text{Eq. 15})$$

Where w_i = Share of energy consumed by component i.

We can see that the growth rate of total energy is the energy-weighted average of the growth rate of each of the factors:

$$\frac{d \ln E}{dt} = \sum_i w_i \left[\frac{d \ln A}{dt} + \frac{d \ln S_i}{dt} + \frac{d \ln I_i}{dt} \right] \quad (\text{Eq. 16})$$

While equation 16 holds instantaneously, it must be integrated over a discrete time period to yield a useable result. In general terms, this integration over the interval 0 to T generates

$$\begin{aligned} \ln(E_T / E_0) &= \sum_i \int_0^T w_i \frac{d \ln A}{dt} dt && [\text{Activity effect } (D_{act})] \\ &+ \sum_i \int_0^T w_i \frac{d \ln S_i}{dt} dt && [\text{Structural effect } (D_{str})] \\ &+ \sum_i \int_0^T w_i \frac{d \ln I_i}{dt} dt && [\text{Intensity effect } (D_{int})] \end{aligned} \quad (\text{Eq. 17})$$

The logarithmic or percentage change in total energy consumption between any two points in time (D_{tot}) can therefore be decomposed into three effects.

$$D_{tot} \sim D_{act} + D_{str} + D_{int} \quad (\text{Eq. 18})$$

An approximate solution to these integrals can be obtained by selecting an appropriate function of the end points at time 0 and T (D_{tot}) is an approximation because of the residual). This results in the following general expressions for each of the effects

$$D_{act} = \left(\sum_i w_i^* \right) \ln(A_T / A_0) \quad (\text{Eq. 19})$$

$$D_{str} = \sum_i w_i^* \ln(S_{i,T} / S_{i,0}) \quad (\text{Eq. 20})$$

$$D_{int} = \sum_i w_i^* \ln(I_{i,T} / I_{i,0}) \quad (\text{Eq. 21})$$

Depending upon the nature of the solution method, the three effects may not exactly sum to the total change, yielding a small residual term in equation 18. A solution yielding no residual term is defined as perfect decomposition where residuals are blended in the coefficients of the total change.

The weights w_i^* in equations 19 – 21 are derived by an averaging of the initial and terminal shares of energy used in each of the components. How this averaging is performed reflects an assumption about the unobserved path of the variables A , S , and I between the initial and end periods. The most straightforward assumption is to assume that the path is linear between the end points; in this case the weights are defined

$$w_i^* = (w_{i,0} + w_{i,T}) / 2 \quad (\text{Eq. 22})$$

The choice of these weights results in what has been termed an Arithmetic mean Divisia approach. While easy to apply, this is an imperfect decomposition method and normally results in a small residual in equation 18; thus the sum of the three effects may not precisely equal the total change in energy use.

Ang and Choi [1997] proposed an advanced Divisia method that results in no residual, and thus yields a perfect decomposition of the effects. Their solution was to base the weights on what is termed a logarithmic mean function of the shares. The logarithmic mean of any two variables is defined as

$$L(x,y) = (y - x)/\ln(y/x) \quad (\text{Eq. 23})$$

As applied to the energy consumption shares, the logarithmic mean function is defined

$$L(w_{i,0}, w_{i,T}) = (w_{i,T} - w_{i,0}) / \ln(w_{i,T} / w_{i,0}) \quad (\text{Eq. 24})$$

The final weights w_i^* are based upon a normalization that ensures that they exactly sum to one:

$$w_i^* = L(w_{i,0}, w_{i,T}) / \sum_i L(w_{i,0}, w_{i,T}) \quad (\text{Eq. 25})$$

Lermit and Jollands [2001] provide a proof that this formulation of the weights yields no residual term, regardless of how the specific values of the variables vary over time.

The use of the logarithmic mean Divisia method implies that all of the variables are growing at constant growth rates between the initial and terminal periods. Thus, the method assumes that unobserved values between the two periods lie on a path defined by an exponential growth curve.

2.5.5 Construction of Time Series Index Decomposition Method

While the Divisia index decomposition method can be applied over any time period, it is applied to annual observations in this system of energy intensity indicators. The logarithmic change in energy use between each pair of successive years is decomposed using the log mean Divisia method, yielding the terms shown in equation 18. By implicitly setting the first of the two years equal to 1.0, an index number for the second year is obtained by taking the exponential of each of the terms as follows:

$$\begin{aligned}\text{Exp}(D_{eng}) &= \text{Exp}(D_{act} + D_{str} + D_{int}) \\ &= (I_{act}) \cdot (I_{str}) \cdot (I_{int})\end{aligned}\tag{Eq. 26}$$

where

$$I_{act} = \text{Exp}(D_{tot}), I_{str} = \text{Exp}(D_{str}), \text{ and } I_{int} = \text{Exp}(D_{int}),$$

$$I_{act} = \text{Activity index, year-over-year,}$$

$$I_{str} = \text{Structure index, year-over-year,}$$

$$I_{int} = \text{Intensity index, year-over-year.}$$

For each effect, the indexes are then chained to form a time series for the available data period.

Ang [1998] introduces the method of factorizing changes in energy and environmental indicators through decomposition because of the following:

1. Perfect decomposition,
2. Factor changes in energy demand or gas emissions,
3. Handle zero values in data sets.

Ang [1998] also indicates that the main objective of decomposition analysis is to quantify various underlying factors that contribute to changes in energy and environmental indicators over time. Two common approaches are decomposition of an aggregate index (energy intensity approach) where the aggregate index is given by dividing the aggregate intensity of one year, such as the ratio of industrial energy demand to industrial output.

This leads to estimates of factorized effects given in indexes. The other approach is the decomposition of differential quantity (consumption approach). This decomposition is a direct decomposition of a change in energy demand or gas emissions between two different years in physical terms. This change of quantity is given in the chosen measurement unit for energy demand or gas emissions,

2.6 Conclusion

Index decomposition methods have been used to study energy usage for decades. The most widely used ones are derived from Divisia and Laspeyres index methodologies. This research seeks to extend the use of these methodologies into plant level studies to study the impacts of main energy consuming equipment to the total plant wide energy usage from a production and financial view.

CHAPTER III

STATEMENT OF RESEARCH

3.1 Problem Statement

There is a need for a standard methodology to develop a facility-level energy performance monitoring index that is independent of product mix that can be used to identify the energy-side production efficiency as the product is being produced as well as the ability to monitor the changes of that measure over a period of time as part of a real-time commissioning and re-commissioning effort.

3.2 Research Goals

There is a need for more effective facility-level energy performance monitoring that is independent of product mix. The goal of this research is to address this problem by focusing on the following:

1. Develop an index number decomposition methodology to use as a facility-level energy performance monitoring index from existing higher level index number decomposition methodologies.
2. Use the developed index number to identify the energy-side production efficiencies over time and that, with additional research, can be used to monitor the efficiency changes over a period of time as a part of a real-time commissioning and re-commissioning effort.

3.3 Major Research Tasks

To accomplish the goals, the major research tasks are identified as followed

1. Study the available index decomposition methodologies and select the potential ones to study in detail and use as a prototype to modify and use at the plant level.
2. From the selected existing energy intensity index methodologies, develop procedures to use the intensity index number as a facility-level energy performance monitoring.
3. Evaluate the methodology by using actual data by developing a simulation model which mimics a brick manufacturing plant. The simulation model uses equations from Jeschar and Bittner [1989] and evaluated by comparing the data output of the model with published journals on brick energy consumption by Prasertsan et al [1995], and Prasertsan and Theppaya [1995]. The energy intensity index is then used to monitor the energy usage. The model also reflects various weather, product mix, and efficiency deterioration scenarios.

3.4 Research Boundaries

1. The manufacturing plants presented in this research refer to manufacturing plants with flow shop or continuous flow production of one product type at a time or with the capability to sub-meter the individual product lines. Specifically, a brick manufacturing model is used in this research.
2. Index methodologies explored in this research are limited to Divisia and Laspeyres techniques due to their popularity in the past decade (see literature review).
3. The research will also recognize the weather impact.

CHAPTER IV

METHODOLOGY

4.1 Introduction

The goal of this research is to develop an energy index decomposition methodology used at the plant level to use as an energy performance monitoring tool. The research utilizes the existing sector time series index decomposition methods to generate an energy intensity index at the plant level. Traditional systems of energy intensity indicators are designed to track the changes in energy intensity for a total country's economy, broad end use sectors, and sub-sectors. The proposed research will study the existing index number decomposition methodologies as plant-level energy utilization monitoring tools.

4.2 Research Plan

To accomplish the goal and objectives described above, the research was broken into phases.

Phase I: Develop procedures to systematically identify input variables to be used as the facility's energy monitoring input.

Task 1 Develop a simple plant energy consumption model. The information needed is composed of historical data collected monthly over the past 3 years as follows:

1. Product type,
2. Quantity produced,
3. Cost of goods sold associated with each product type,
4. Monthly energy usage.

Task 2 Define product output as the number of production units and energy intensity as energy used per unit of production.

Task 3 Identify sources of process energy input (electricity, natural gas, other fuel).

Task 4 Develop a plant energy model to test the sensitivity of the indexes against

1. Trending (steepness)
 - a. Mild
 - b. Moderate
 - c. Strong
2. Weather impact
 - a. Mild (Houston, TX)
 - b. Moderate (Oklahoma City, Oklahoma)
 - c. High (Minneapolis, Minnesota)
3. Product mix and effects of product mix toward energy intensity index
 - a. Equally produced
 - b. High intensity
 - c. Low intensity

Phase II: Select the index decomposition methodologies

Task 1 Define the potential existing index decomposition methodologies to be used in this research as Log Mean Divisia Additive method and Refined Laspeyres energy intensity approaches.

Task 2 Use an S+ program⁴ to fit a time series ARIMA model to each index decomposition methodology and use AIC (Akaike Information Criterion), explained in Chapter 6 to justify the best model for each index. From the fitted model, plot the innovation (residual) by using S+. Acceptable time series models should have low AIC and random

⁴ S+ or SPLUS is a statistical software (language similar to MATLAB) developed by Insightful Inc. mainly used to analyze time series and predictive statistics

innovation plots. Tests of randomness will follow the Ljung-Box test at 95% confidence level explained in Chapter 6. Select 3 out of 7 methodologies that have the least complicated forms of ARIMA model and highest average absolute amplitude (most sensitive) when plotted on a time series graph.

Phase III: Test the index methodologies on a model

Test the proposed index decomposition methodology on the actual data obtained from a brick manufacturing model developed by Jeschar and Bittner [1989].

Phase IV: Formulate framework for future research

In future research, this methodology is potentially useful as a time series production energy efficiency monitoring tool to detect irregularities in production energy usage or as a part of a real-time commissioning effort. Specific ideas with respect to these potential uses will be documented.

Proposed usage of Index Decomposition Methods (ID)

Since the concept presented in this research is similar to the application of index numbers to study the contributions of price and quantity levels to changes in aggregate commodity consumption, we present an index decomposition methodology (ID) framework using the index number concept. In general, ID can be performed as long as the aggregate indicator being studied, V , can be expressed in the form:

$$V = \sum_i^m X_{i1}X_{i2}...X_{in} \quad \text{where } i=1, 2, \dots, n \quad (\text{Eq. 27})$$

where the first subscript of X denotes the i^{th} sector among a total of m sectors and the second subscript denotes n different factors. The purpose of ID is to decompose a change in V into individual effects associated with the variation of each of the factors X_{i1} , X_{i2} , ..., X_{in} [Ang and Zhang 2000]. This research will focus on two of the most popular indexes, Log Mean Divisia, and refined Laspeyres indexes proposed by Sun [1998].

Log Mean Divisia Index (LMDI)

The Log Mean Divisia index technique in additive form was proposed by Ang et al. [1998] and multiplicative form by Ang and Lui [2001]. These are commonly referred to as LMDI I. Ang and Choi [1997] and Ang et al. [2003] proposed LMDI II additive and multiplicative respectively. Both are perfect decomposition techniques which yield no residuals, the only difference is the weight function.

Let

$$V_i = \sum_i X_{1i} X_{2i} \dots X_{ni} \quad ; i= 1, 2, \dots, n \quad (\text{Eq. 28})$$

Where V_i = Aggregate of interest i , which composed of n factors
 X = Attributes of interest (subscript i) denotes an attribute of the aggregate such as energy consuming sector, fuel type, etc.

Therefore, from year 0 to year T ; the aggregate changes from

$$V^0 = \sum_i x_{1i}^0 x_{2i}^0 \dots x_{ni}^0 \quad (\text{Eq. 29})$$

to $V^T = \sum_i x_{1i}^T x_{2i}^T \dots x_{ni}^T \quad (\text{Eq. 30})$

We then have in perfect decomposition

Multiplicative

$$D = V^T/V^0 = D_{x1} \cdot D_{x2} \dots \cdot D_{xn} \quad (\text{Eq. 31})$$

Additive

$$\Delta V = V^T - V^0 = \Delta V_{x1} + \Delta V_{x2} + \dots + \Delta V_{xn} \quad (\text{Eq. 32})$$

where

D = Multiplicative decomposition of changes via Divisia index,

ΔV = Additive decomposition of changes via Divisia index.

Based on the proposed decomposition methodology by Ang et al. [1998] and Ang and Lui [2001] the LMDI I formula is as follows

LMDI I (multiplicative)

$$D_{xk} = \exp \left(\sum_i \frac{L(V_i^T, V_i^0)}{L(V^T, V^0)} \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \right) \quad (\text{Eq. 33})$$

LMDI I (additive)

$$\Delta V_{xk} = \sum_i L(V_i^T, V_i^0) \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \quad (\text{Eq. 34})$$

Based on the proposed decomposition methodology by Ang and Choi [1997] and Ang et al. [2003], the LMDI II formula is as follows:

LMDI II (multiplicative)

$$D_{xk} = \exp \left(\sum_i \frac{L(w_i^T, w_i^0)}{\sum_j L(w_j^T, w_j^0)} \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \right) \quad (\text{Eq. 35})$$

LMDI II (additive)

$$\Delta V_{xk} = \sum_i \frac{L(w_i^T, w_i^0)}{\sum_j L(w_j^T, w_j^0)} L(V^T, V^0) \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \quad (\text{Eq. 36})$$

where

$$w_i^T = V_i^T / V^T,$$

$$w_i^0 = V_i^0 / V^0,$$

$L(a, b)$ = the logarithmic average of two positive numbers a and b given by

$$\begin{aligned} L(a, b) &= \frac{a - b}{\ln a - \ln b} \quad \text{for } a \neq b \\ &= a \quad \text{for } a = b \end{aligned} \quad (\text{Eq. 37})$$

As mentioned earlier, the LMDI I and LMDI II are similar and the only difference is the weight function as followed:

Multiplicative decomposition:

$$D_{xk} = \exp \left(\sum_i W_i^* \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \right) \quad (\text{Eq. 38})$$

Additive decomposition:

$$\Delta V_{xk} = \sum_i W_i^* L(V^T, V^0) \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \quad (\text{Eq. 39})$$

where

$$W_i^* = L(V_i^T, V_i^0) / L(V^T, V^0) \text{ in LMDI I,}$$

$$W_i^* = L(w_i^T, w_i^0) / \sum_j L(w_j^T, w_j^0) \text{ in LMDI II.}$$

Refined Laspeyres Technique

The refined Laspeyres technique is an improved Laspeyres technique and was improved by Sun [1998]. The Refined Laspeyres is only available in the additive decomposition method (no multiplicative technique research published to date).

The total change in aggregate energy intensity can be written as

$$\begin{aligned}\Delta I_{tot} &= \sum_i S_{i,T} I_{i,T} - \sum_i S_{i,0} I_{i,0} \\ &= \sum_i (S_{i,T} - S_{i,0}) I_{i,0} + \sum_i (I_{i,T} - I_{i,0}) S_{i,0} + \sum_i (S_{i,T} - S_{i,0})(I_{i,T} - I_{i,0}) \quad (\text{Eq. 40})\end{aligned}$$

where

- E_t = Total industrial energy consumption,
- $E_{i,t}$ = Energy consumption in industrial sector i ,
- Y_t = Total industrial production,
- $Y_{i,t}$ = Total industrial production sector i ,
- $S_{i,t}$ = Production share of sector i ($= Y_{i,t}/Y_t$),
- I_t = Aggregate energy intensity ($= E_t/Y_t$),
- $I_{i,t}$ = Energy intensity of sector i ($= E_{i,t}/Y_{i,t}$).

Note that ΔI is similar to ΔV of the Divisia additive decomposition method but is an aggregate intensity where as ΔV is an aggregate of the indicator being studied (intensity included).

When the variations in variables S_i and I_i are large, the residual/interaction is large. By splitting it equally between the two main effects, the formulae become:

$$\Delta I_{str} = \sum_i (S_{i,T} - S_{i,0}) I_{i,0} + \frac{1}{2} \sum_i (S_{i,T} - S_{i,0})(I_{i,T} - I_{i,0}) \quad (\text{Eq. 41})$$

$$\Delta I_{int} = \sum_i (I_{i,T} - I_{i,0}) S_{i,0} + \frac{1}{2} \sum_i (S_{i,T} - S_{i,0})(I_{i,T} - I_{i,0}) \quad (\text{Eq. 42})$$

where

E_t = Total industrial energy consumption,

$E_{i,t}$ = Energy consumption in industrial sector i ,

Y_t = Total industrial production,

$Y_{i,t}$ = Total industrial production sector i ,

$S_{i,t}$ = Production share of sector i ($= Y_{i,t}/Y_t$),

I_t = Aggregate energy intensity ($= E_t/Y_t$),

$I_{i,t}$ = Energy intensity of sector i ($= E_{i,t}/Y_{i,t}$).

CHAPTER V

PLANT LEVEL ENERGY CONSUMPTION MODEL DEVELOPMENT

5.1 Introduction

In order to study the energy intensity index according to Chapter 4, a plant level energy consumption model needs to be constructed.

As defined in Chapter 4, one of the well known flow-shop process is brick manufacturing process. The process is relatively straightforward.

5.2 Brick manufacturing process and building the model

Process understanding [Kolarik 1999] helps a researcher gain insights of how energy is being used in the process and permits identification of critical variables (leverages) associated with energy usage.

A Brick manufacturing process⁵ includes mixing ground clay with water, forming them into the desired shapes, then drying and firing them. There are six general phases in making bricks shown in Figure 3 on the next page

1. winning and storage of raw materials (shale clay),
2. preparing raw materials (crushing, grinding, screening and classifying),
3. forming units,

⁵ <http://www.bia.org/BIA/technotes/t9.htm>

4. drying,
5. kiln firing and cooling,
6. drawing and packing finished products.

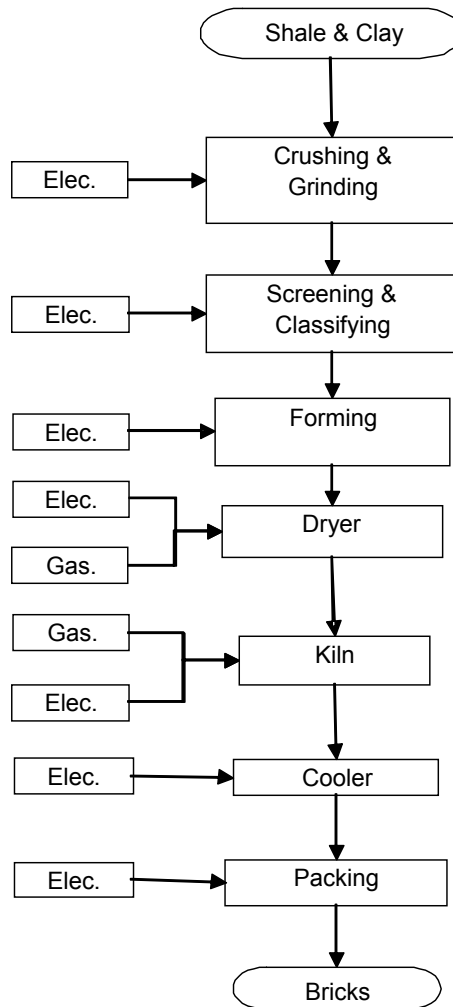


Figure 3 Diagrammatic representation of brick manufacturing process

Winning and Storage

Surface clays, shales and some fire clays are mined in open pits with power equipment.

The clay or shale mixtures are then transported to plant storage areas. It is common practice to store enough raw materials for several days' operations. The materials then go through the blending process for more uniform raw materials, helps to control color and

permits some control over raw material suitability for manufacturing a given type of brick.

Preparation

The clay is crushed to break up large chunks and remove stones then ground prior to mixing other raw material. Most plants then screen the clay, passing it through inclined vibrating screens to control particle sizes.

Forming

The material goes to the Tempering process which produces a homogeneous, plastic mass ready for molding. It is most commonly achieved by adding water to the clay in a pug mill, a mixing chamber which contains one or more revolving shafts with blades. After pugging, the now plastic clay mass is ready to go to the forming step. At the present time, there are three principal processes for forming brick: the stiff-mud, the soft-mud and the dry-press processes.

Extrusion process

In the stiff-mud process (extrusion process), clay is mixed with only sufficient water to produce plasticity, usually from 12 to 15 percent by weight. After thorough mixing, i.e., "pugging", the tempered clay goes through a de-airing chamber in which a vacuum of 15 to 29 in. (375 to 725 mm) of mercury is maintained. De-airing removes air holes and bubbles, giving the clay increased workability and plasticity, thus resulting in greater strength.

Next, the clay is extruded through a die to produce a column of clay in which two dimensions of the final unit are determined. The column then passes through an automatic cutter to make the final dimension of the brick unit. As the clay column leaves the die, textures or surface coatings may be applied.

Drying process

When wet clay units come from molding or cutting machines, they contain from 7 to 30 percent moisture, depending upon the forming method. Before the firing process begins,

most of this water is evaporated in dryer chambers at temperatures ranging from about 100°F to 400°F (38°C to 204°C). Drying time, which varies with different clays, is usually from 24 to 48 hr. Although heat may be generated specifically for dryer chambers, it is more commonly supplied as exhaust heat from firing kilns. In all cases, heat and humidity must be carefully regulated to avoid excessive cracking in the product.

Firing and Cooling. Firing, one of the most specialized steps in the manufacture of brick, requires from 40 to 150 hr. depending upon kiln type and other variables. Several kilns are in use, the chief types being tunnel and periodic kilns. Fuel may be natural gas, coal, oil, sawdust, propane or combinations of these fuels.

Dried units are set in periodic kilns according to a prescribed pattern that permits free circulation of hot kiln gases. A periodic kiln is one that is loaded, fired, allowed to cool and unloaded, after which the same processes are repeated. In a tunnel kiln, units are similarly loaded on special cars which pass through various temperature zones as they travel through the tunnel. The heat conditions in each zone are carefully controlled and the kiln operates continuously.

Firing may be divided into six general stages: 1) water-smoking (evaporating free water), 2) dehydration, 3) oxidation, 4) vitrification, 5) flashing and 6) cooling. All except flashing and cooling are associated with rising temperatures in the kiln. Although the actual temperatures will differ with the clay or shale, water-smoking takes place at temperatures up to about 400°F (204°C), dehydration from about 300°F to 1,800°F (149°C to 982°C), oxidation from 1000°F to 1800°F (538°C to 982°C) and vitrification from 1,600°F to 2,400°F (871°C to 1,316°C).

The rate of temperature change must be carefully controlled, depending on the raw materials, as well as the units being produced. Kilns are normally equipped with recording pyrometers or other temperature sensors to provide a constant check on the firing process. Near the end of the firing process, the units may be "flashed" to produce color variations.

After the temperature has reached the maximum and is maintained for a prescribed time, the cooling process begins. Forty-eight to 72 hr are required for proper cooling in periodic kilns; but in tunnel kilns, the cooling period seldom exceeds 48 hr. Because the rate of cooling has a direct effect on color and because excessively rapid cooling will cause cracking and checking of the ware, cooling is an important stage in the firing process.

Drawing. Drawing is the process of unloading a kiln after cooling. It is at this stage that units are sorted, graded, packaged and taken to a storage yard or loaded onto rail cars or trucks for delivery. The majority of brick today are packaged in self-contained, strapped cubes, which can be broken down into individual strapped packages for ease of handling on the jobsite. The packages and cubes are formed in such a manner as to provide openings for handling by fork lifts. Brick manufactured and selected to produce characteristic architectural effects resulting from non-uniformity in size, color and texture may not lend themselves to self-contained packaging, and are usually shipped on wooden pallets.

5.3 Brick Model Construction and Evaluation

When building a process model, there are two fundamental issues that need to be explored simultaneously, general principles and specific variables [Kolarik 1999]. Brick manufacturing uses various technologies but the major principle is a process of converting clay into brick via thermo reactions in the kiln (fusion process). Several major variables play a role in this process namely brick type, outside air condition, and processing time. Table III on the next page shows general brick energy intensity. The table shows that the kiln process uses approximately 90% of total energy usage. For simplification, the model can be reduced to the kiln process.

TABLE III
BRICK ENERGY CONSUMPTION [BROWN 1996]

No.	Process	Subprocess	Elec. (Btu/lb)	Gas(Btu/lb)	Total (Btu/lb)	% energy usage
1	Crushing		10		10	0.4%
2	Screening	Separation	3		3	0.1%
3	Forming	Extrusion	61		61	2.3%
		Soft plastic forming	61		61	2.3%
		Dry press forming	61		61	2.3%
4	Drying		2	29	31	1.2%
5	Kiln		64	2300	2364	89.9%
6	Cooling		36		36	1.4%
7	Packing		2		2	0.1%
Total					2629	100.0%

Kiln, dryer, and cooler mass and energy equation by Jeschar and Bittner [1989] of the process is

$$\begin{aligned} \dot{m}_B \cdot h_u &= \dot{m}_S \cdot C_{S,3-1} \cdot (T_{S3} - T_U) + \dot{m}_T \cdot C_{T,3-1} \cdot (T_{t3} - T_U) + \dot{m}_S \cdot \Delta h_R \\ &+ \dot{m}_{G1} \cdot C_{G,1-U} (T_{G1} - T_U) + \dot{m}_{LE} \cdot C_{L,E-U} (T_{LE} - T_U) + \dot{Q}_v \end{aligned} \quad (\text{Eq. 43})$$

Where

\dot{m}_B = Mass flow rate of natural gas in kg/second

\dot{m}_S = Mass flow rate of brick in kg/second

\dot{m}_T = Mass flow rate of transport in kg/second

\dot{m}_{G1} = Mass flow rate of gas in kg/second

\dot{m}_{LE} = Mass flow rate of air out of the kiln in kg/second

h_u = Lower calorific value (lower heating value) of natural gas in kJ/kg

$C_{S,3-1}$ = Specific heat of brick in kJ/kg-sec

$C_{T,3-1}$ = Specific heat of transport in kJ/kg-sec

$C_{G,1-U}$ = Specific heat of gas in kJ/kg-sec

$C_{L,E-U}$	= Specific heat of air in kJ/kg-sec
T_{S3}	= Temperature of brick at stage 3 in °C
T_{G1}	= Temperature of gas at stage 1 in °C
T_U	= Ambient temperature in °C
T_{t3}	= Temperature of transport at state 3 in °C
T_{LE}	= Temperature of air exiting in °C
T_k	= Temperature of kiln in °C
T_D	= Temperature of brick exiting the dryer in °C
η	= Overall kiln efficiency (includes but not limited to heat loss and combustion)
Δh_R	= Specific reaction enthalpy during the drying process
\dot{Q}_v	= Kiln energy consumption in kJ/second
\dot{Q}_l	= Heat loss

By only focus on the kiln, Equation 43 can be modified into Equations 44 and 45.

$$\dot{m}_G = \left[\dot{m}_S \cdot C_S \cdot (T_k - T_D) + \dot{m}_T \cdot C_T \cdot (T_k - T_D) \right] \cdot [C_G \cdot (1,778 - T_k - T_{LE})]^{-1} \quad (\text{Eq. 44})$$

$$\dot{Q}_k = \left[\dot{m}_G \cdot C_G (25 - T_U) + \dot{m}_S \cdot C_S \cdot (T_k - T_D) + \dot{m}_T \cdot C_T \cdot (T_k - T_D) \right] \cdot \frac{1}{\eta} \quad (\text{Eq. 45})$$

The kiln model is constructed in S-Plus, assuming bake time of 48 hours. In order to study the process leverages, the model composed of three variations, weather impact, product mix impact, and efficiency (trending) impact. Weather impact uses average daily outside temperature of three locations for mild, medium, and high at near sea levels.

These locations are as followed

Mild climate impact:	Houston, TX
Medium climate impact:	Oklahoma City, OK
High climate impact:	Minneapolis, MN

Production mix impact studies the variation in energy consumption due to changes in product mix. In general, brick bake temperatures can vary from 800°C to 1200°C depending on the product requirements. In this model, temperatures of the kiln are set at

Product type 1: 900°C

Product type 2: 1,000°C

Product type 3: 1,100°C

The model is set to run at three product mixtures, high, medium, and low for 48 hours (2 days). A uniform distribution random number generator is used to generate production schedules composed of three product types. The product mix with high temperature requirements composed of 50% more chance of product type 3 than the other two. The product mix with medium temperature requirement has an equal chance of producing all three products, and product mix with low temperature requirement has 50% more chance of product type 1 than the other two.

One of the objectives of this research is to study the efficiency deterioration over time. An artificial trend is created to test the response of the brick model. The trend increases overtime (efficiency decreases). Initial efficiency was set at 80%. Trend increases in a straight line manner over 3 years in 3 levels, mild, medium, and high.

The model validation is done by compare the energy intensity of the output in kJ/kg to brick energy intensity studies by Jeschar and Bittner [1989], Prasertsan et al [1995], and Prasertsan and Theppaya [1995]. Name convention of the calculated energy intensity index is as follows:

<u>Index</u>	<u>Intensity</u>	<u>Ambient temp</u>	<u>Trend</u>	<u>Product mix</u>
L, A	I	H, M, L	H, M, L	H, M, L

L: Laspeyres index (first digit only)

A: Log Mean DivisiA index

I: Intensity

H: High

M: Medium

L: Low

For example, LIHML represents Laspeyres intensity index for high ambient temperature impact (Minneapolis, MN), medium efficiency deterioration, and composed mostly with product with low temperature kiln requirements. Full simulation scenarios are shown in Table IV and V.

TABLE IV
SIMULATION SCENARIOS FOR REFINED LASPEYRES ADDITIVE ENERGY INTENSITY INDEX

Mix Small		Trend		
		Small	Medium	Large
Weather	Small	LILLL	LILML	LILHL
	Medium	LIMLL	LIMML	LIMHL
	Large	LIHLL	LIHML	LIHHL

Mix medium		Trend		
		Small	Medium	Large
Weather	Small	LILLM	LILMM	LILHM
	Medium	LIMLM	LIMMM	LIMHM
	Large	LIHLM	LIHMM	LIHHM

Mix Large		Trend		
		Small	Medium	Large
Weather	Small	LILLH	LILMH	LILHH
	Medium	LIMLH	LIMMH	LIMHH
	Large	LIHLH	LIHMH	LIHHH

TABLE V
SIMULATION SCENARIOS FOR LOG MEAN DIVISIA ADDITIVE ENERGY INTENSITY INDEX

Mix Small		Trend		
		Small	Medium	Large
Weather	Small	AILLL	AILML	AILHL
	Medium	AIMLL	AIMML	AIMHL
	Large	AIHLL	AIHML	AIHHL

Mix medium		Trend		
		Small	Medium	Large
Weather	Small	AILLM	AILMM	AILHM
	Medium	AIMLM	AIMMM	AIMHM
	Large	AIHLM	AIHMM	AIHHM

Mix Large		Trend		
		Small	Medium	Large
Weather	Small	AILLH	AILMH	AILHH
	Medium	AIMLH	AIMMH	AIMHH
	Large	AIHLH	AIHMH	AIHHH

5.4 Calculation Example

Table VI shows an example of a manufacturing plant which produces two product types in two years period. In year 0, Product type 1 used 8 MBtu (8,000 Btu) of energy to produce 10 pounds of product and Product type 2 used 20 MBtu of energy to produce 40 pounds of product. This resulted in energy intensity to produce product type 1 and types 2 are 0.8 and 0.5 respectively. We can observe that product type 1 is more energy intensive (energy used per pounds of product) than product type 2. In year 1, Product type 1 used 35 MBtu of energy to produce 50 pounds of product and Product type 2 used 16 MBtu of energy to produce 40 pounds of product. Both energy intensities of both products reduce from 0.8 to 0.7 for product type 1 and 0.5 to 0.4 for product type 2. However, the total facility energy intensity increases by from 0.56 to 0.57.

TABLE VI
EXAMPLE CALCULATIONS OF REFINED LASPEYRES AND LOG MEAN DIVISIA INDEXES

E = Energy consumption (MBtu) Y = Production (Lb) S = Production share of product types I = Aggregate energy intensity								
	Year 0				Year 1			
	E0	Y0	S0	I0	ET	YT	ST	IT
Product type 1	8	10	0.20	0.8	35	50	0.56	0.7
Product type 2	20	40	0.80	0.5	16	40	0.44	0.4
Plant wide	28	50	1	0.56	51	90	1	0.57

After applying plant level additive index decomposition methods shown in Table VII on the next page Figure 4 on the following page confirmed that there has been an increase in the plant level energy intensity as shown that the index (ΔI_{tot}) is positive. The structural energy intensity indexes (ΔI_{str}) for both are positive. This reflects the increase in energy intensity (0.11 and 0.10) of the product mix (product type 1 and product type 2).

However, the energy intensity indexes ΔI_{int} of both Refined Laspeyres and Log Mean Divisia are negative (-0.1 and -0.096 respectively) which indicated that the overall plant has improved in production energy efficiency.

TABLE VII
EXAMPLE CALCULATIONS OF REFINED LASPEYRES AND LOG MEAN DIVISIA INDEXES

Index Decomposition (Additive)		
	Refined Laspeyres	Log Mean Divisia
ΔI_{tot}	0.007	0.007
ΔI_{str}	0.11	0.10
ΔI_{int}	-0.100	-0.096

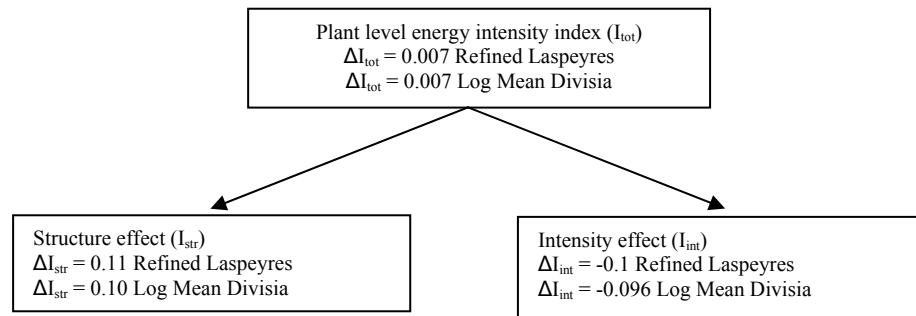


Figure 4 Decomposition of total energy intensity into structure and intensity effects

From the example we can conclude that due to the expansion of production share of product type 1, which is a more energy intensive than product type 2, the plant aggregate energy intensity increase by 0.7%. Despite improvements in energy efficiency (negative value) as reflected by the changes in overall production energy intensity (ΔI_{int}). Since the impact of changes in production mix is more significant, it leads to an increase in aggregate energy intensity.

CHAPTER VI

STATISTICAL VALIDATION PROCESS

6.1 Introduction

This chapter introduces the statistical techniques to be used to validate the energy intensity indexes as mentioned in the Statement of Research. The objectives of using these techniques are to show that the index can be used to monitor the production efficiency without the influence of product mix. This can be achieved by performing correlation test between intensity index and the production mix. The chapter also proposes a standardize process of using energy intensity index to monitor the “bare” efficiency by fitting ARIMA models.

6.2 Statistical Test Procedure

After the indexes are determined through the brick model, they are tested according to Phase II in Chapter 4. The tests include the following

1. Energy intensity index selection between Refined Laspeyres Additive method and Log Mead Divisia Additive method
2. Show that the intensity index does not have the influence of product mix. In other words, the changes in product type do not affect the energy intensity index. This can achieve by performing Pearson’s test of correlation.
3. Fit the intensity index to time series ARIMA (Auto Regressive Integrated Moving Average) model.

Test of Correlation

Test the correlation between the Intensity index and the changes due to product type. Use the Pearson's Test of Correlation with

H_0 : There is no correlation between intensity index and product types $\rho=0$

H_a : There is a correlation between intensity index and product types $\rho \neq 0$

In this dissertation, Pearson's test of correlation is being used to measure the relation between two variables, energy intensity index and product types produced. Correlation coefficients (ρ) range from -1.00 to +1.00 where negative correlation coefficients represent negative correlation (-1.00 represents a perfect negative correlation) and positive correlation coefficients represent positive correlation (+1.00 represents a perfect positive correlation). A correlation coefficient of 0.00 represents a lack of correlation.

Pearson correlation (Simple Linear Correlation) was selected because it assumes that the two variables are measured on at least an interval scale. The correlation coefficient does not depend on the specific measurement units used; for example, the correlation between height and weight will be identical regardless of whether inches and pounds, or centimeters and kilograms are used as measurement units.

The test statistic for correlation test is the P-value at 95% level of significance. If the P-value is less than or equal to 0.05, reject H_0 which means that there is evidence of correlation between intensity index and changes in product type. If P-value is over 0.05, fail to reject the null hypothesis, which means that there is no correlation between the intensity index and changes in product type

Fitting ARIMA Model⁶

The goal of the research is to establish ground work for forecasting the need for re-commissioning of an industrial facility. ARIMA (Auto Regressive Integrated Moving Average) models are one of the most general classes of models used for forecasting a time series.

ARIMA Model

ARIMA models are standardized statistical models used to fit time series data in forecasting applications. The model composed of three main parts, AR(auto-regressive), MA (moving average), and I(integrated). AR term represents the prediction of the current value of the time series as a function of the past values, MA is a current value which is a combination of past white noise (forecast errors) values, and I is trending in the time series. The MA term also helps to smooth out short-term fluctuations, thus highlighting longer-term trends or cycles [Chou 1970]. Several forms of ARIMA models are used in industrial engineering applications especially as Statistical Process Control tools. Most notably are Exponentially Weighted Moving Average (EWMA), Exponentially Weighted Moving Deviations (EWMD), and CuSum control charts. EWMA, EWMD, and CuSum charts are considered effective for detecting small sustained shifts in the process [Kolarik 1999]. These techniques are a subset of ARIMA models and contain only the moving average (MA) terms.

In order for a time series to be analyze, some need to be differenced (de-trend) to be made stationary is said to be an "integrated" version of a stationary series. A nonseasonal ARIMA model is classified as an "ARIMA(p,d,q)" model

where

p is the number of autoregressive terms,

d is the number of nonseasonal differences,

q is the number of lagged forecast errors in the prediction equation.

⁶ <http://www.duke.edu/~rnau/411arim.htm>

To fit the appropriate ARIMA model for a time series the series need to be stationary. This can be achieved by detrending or differencing the series (integrated term).

Seasonal ARIMA models

In some cases, the time series exhibit a repetitive pattern. In this research, average daily ambient temperatures in 3 years period exhibit a repetitive pattern. The seasonal part of an ARIMA model has the same structure as the non-seasonal part but the factors operate across multiples of lags (the number of periods in a season). A seasonal ARIMA model is classified as an $ARIMA(p,d,q) \times (P,D,Q)$ model where

P=number of seasonal autoregressive (SAR) terms

D=number of seasonal differences

Q=number of seasonal moving average (SMA) terms

In identifying a seasonal model, the first step is to determine whether or not a seasonal difference is needed, in addition to or perhaps instead of a non-seasonal difference.

If the seasonal pattern is both strong and stable over time (e.g., high in the Summer and low in the Winter, or vice versa), then a seasonal difference should be used.

Differencing

Fitting an ARIMA model is the determination of the order of differencing needed to stationarize the series. Normally, the correct amount of differencing is the lowest order of differencing that yields a time series which fluctuates around a well-defined mean value and whose autocorrelation function (ACF) plot decays fairly rapidly to zero, either from above or below. If the series still exhibits a long-term trend, or otherwise lacks a tendency to return to its mean value, or if its autocorrelations are positive out to a high number of lags (e.g., 10 or more), then it needs a higher order of differencing.

The seasonal difference of a time series is the series of changes from one season to the next. For monthly data, in which there are 12 periods in a season, the seasonal difference

of Y at period t is $Y(t)-Y(t-12)$. In this research, the data are in weekly period. Should seasonal difference is required, the periods are 52 periods in a season.

Model Fit Test

To determine the fit of model, this research uses the Akaike information criterion (AIC) [Akaike 1974]. AIC is a statistical model fit measure which quantifies the relative goodness-of-fit of various previously derived statistical models given a sample of data. It uses a rigorous framework of information analysis based on the concept of entropy. It also examines the complexity of the model together with the goodness of its fit to the sample data to produce a measure which balances between the two in order to prevent over fitting [Wikipedia 2006].

$$AIC = 2k - 2\ln(L) \quad (\text{Eq. 46})$$

where

k is the number of parameters,

L is the likelihood function.

When normally distributed errors are assumed then AIC becomes

$$AIC = 2k - 2\ln \frac{RSS}{n} \quad (\text{Eq. 47})$$

where

n is the number of observations,

RSS is the residual sum of squares.

The preferred model is that with the lowest AIC value. The AIC methodology attempts to find the minimal model that correctly explains the data, which can be contrasted with more traditional approaches to modeling, such as starting from a null hypothesis.

Test of Randomness

After fitting an ARIMA model, the residual needs to be tested for randomness to ensure proper fit. This research uses Ljung-Box statistic test [Shumway and Stoffer 2000] to test residual. The Ljung-Box test is based on the autocorrelation plot and tests the "overall" randomness based on a number of lags. It is often referred to as a "portmanteau" test.

H_0 : The data are random.

H_a : The data are not random.

The test statistic is:

$$Q_{LB} = n(n+2) \sum_{j=1}^h \frac{\rho^2(j)}{n-j} \quad (\text{Eq. 48})$$

Where

n is sample size

$\rho(j)$ is autocorrelation at lag j

h is number of lags being tested

Based on a Chi-square distribution, reject if

$$Q_{LB} > \chi^2_{1-\alpha, h}$$

CHAPTER VII

EXPERIMENTAL RESULTS

Introduction

This chapter shows the results from the model created in Chapter 5 and statistics tests proposed in Chapter 6.

Index Selection

After calculating the two main indexes, Refined Laspeyres and Log Mean Divisia on the results showed that both indexes respond differently to the changes of the model. The indexes were used to monitor weekly the energy intensity changes for three years with the energy intensity of the first week.

From the model, from visually examining the response, Log Mean Divisia appears to respond better to trend input than Refined Laspeyres as shown in Figure 5 (top). After further analysis by differencing both index time series, the Log Mean Divisia response show significant increase in variations of energy intensity compare to Laspeyres shown in Figure 5 (bottom). This increase in variation of all Log Mean Divisia intensity indexes is due to the logarithmic term in the index's formula. The results of the Log Mean Divisia intensity index are consistent through all 27 scenarios shown in Appendix A.

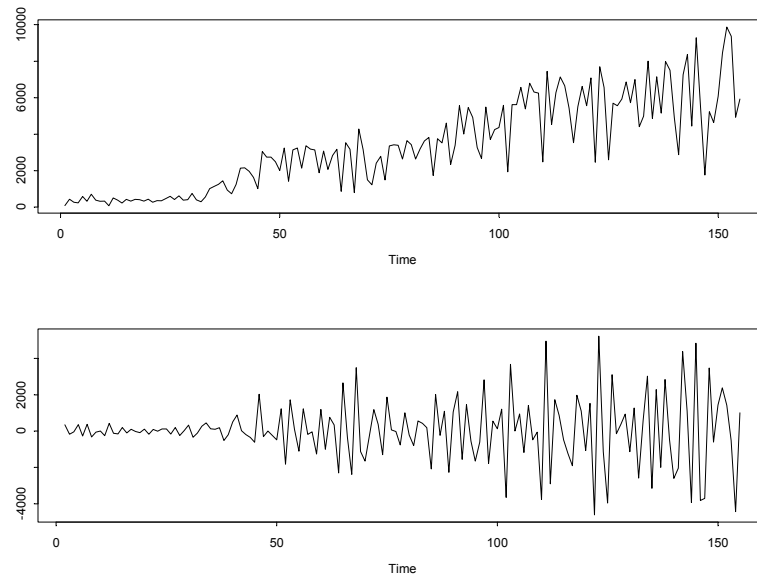


Figure 5 Time series plot of Log Mean Divisia AIHHH (top) and differenced AIHHH (bottom)

The Refined Laspeyres responses are more consistent in magnitude than Log Mean Divisia. Figure 6 shows the response of Refined Laspeyres intensity index of the same data. These results illustrate a pattern that was reflected widely throughout the data.

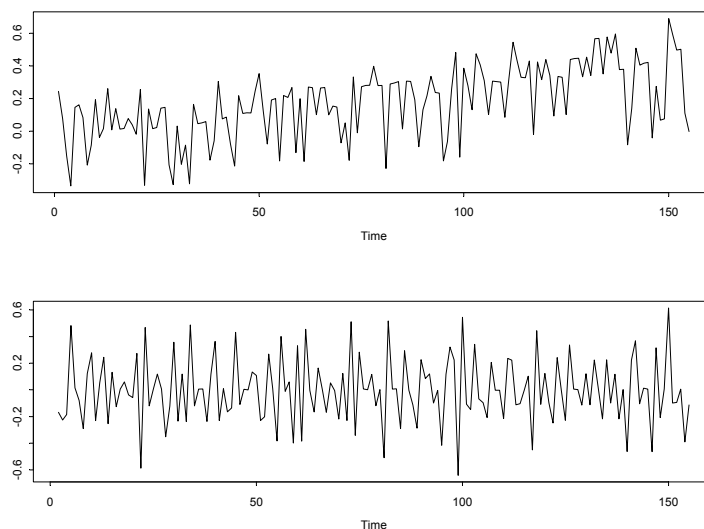


Figure 6 Refined Laspayres intensity index of series plot of LIHHH (above) and differenced LIHHH (below)

Base on this evidence, the Refined Laspeyres is more suitable for plant level long term (three years) monitoring

Correlation Test

H0: There is no correlation between Laspeyres intensity index and production $\rho=0$

H1: There is a correlation between Laspeyres intensity index and production $\rho \neq 0$

The correlation test between the Laspeyres intensity index and production as shown in Table VIII reveal that there is no correlation between the index and the production. This means that the index can be used to monitor the “bare” energy intensity without the influence of the product mix.

TABLE VIII
CORRELATION TEST BETWEEN THE LASPEYRES INTENSITY INDEX AND PRODUCTION

No.	Name	Original Series		Differenced Series	
		CORR	P-Value	CORR	P-Value
1	LIHHH	-0.059	0.463	-0.040	0.618
2	LIMHH	-0.054	0.505	-0.045	0.584
3	LIHMH	-0.052	0.535	-0.049	0.542
4	LIHMM	-0.051	0.523	0.057	0.486
5	LIMMH	-0.044	0.583	-0.053	0.514
6	LIHMM	-0.052	0.519	0.059	0.468
7	LIMHM	-0.055	0.498	0.054	0.491
8	LIMMM	-0.056	0.487	0.056	0.491
9	LILHH	-0.059	0.468	-0.040	0.623
10	LIHLH	-0.039	0.630	-0.057	0.484
11	LIHHL	0.029	0.723	0.061	0.459
12	LILLH	-0.039	0.635	-0.056	0.487
13	LIHLL	0.007	0.927	0.061	0.459
14	LILHL	0.028	0.730	0.061	0.454
15	LILLL	0.007	0.933	0.071	0.379
16	LILMM	-0.047	0.558	0.058	0.474
17	LIMLM	-0.546	0.500	0.058	0.474
18	LIMML	0.015	0.850	0.068	0.400
19	LILLM	-0.044	0.587	0.059	0.464
20	LIMLL	0.005	0.952	0.073	0.368
21	LILML	0.017	0.830	0.067	0.411
22	LIHML	0.018	0.824	0.066	0.416
23	LIMHL	0.026	0.078	0.062	0.441
24	LILMH	-0.050	0.541	0.049	0.546
25	LIHLM	-0.050	0.540	0.061	0.453
26	LIMLH	-0.033	0.680	-0.060	0.461
27	LILHM	-0.048	0.553	0.056	0.494

ARIMA Model Fit

The LIHHH plot has a slight trend as seen in Figure 7 indicate the response to the deterioration of the system efficiency. ACF plot shows that the data are correlated which implies a non-stationary time series.

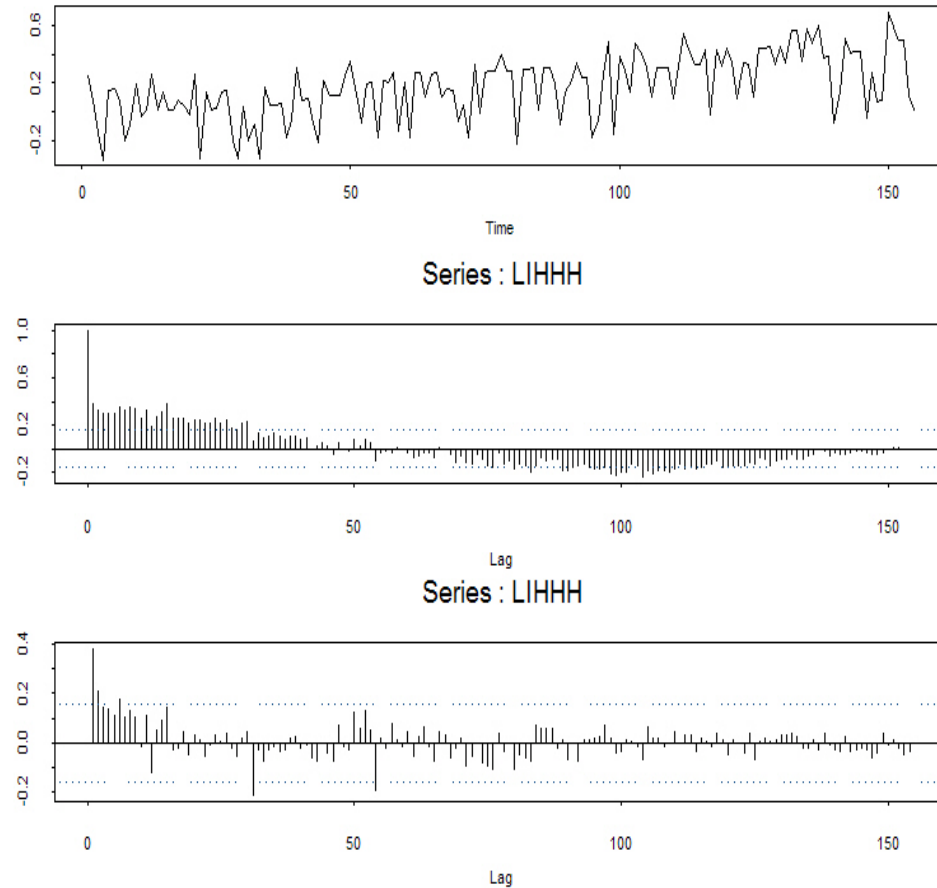


Figure 7 Time series plot (above), ACF plot (middle), and PACF plot (below) of LIHHH

After the non-seasonal differencing, the time series appear more stable as shown in Figure 8. As preliminary analysis, the ACF cuts off at lag =1 and the PACF tails off. According to Shumway and Stoffer [2000] suggest initial guess for ARIMA(0,1,1) model.

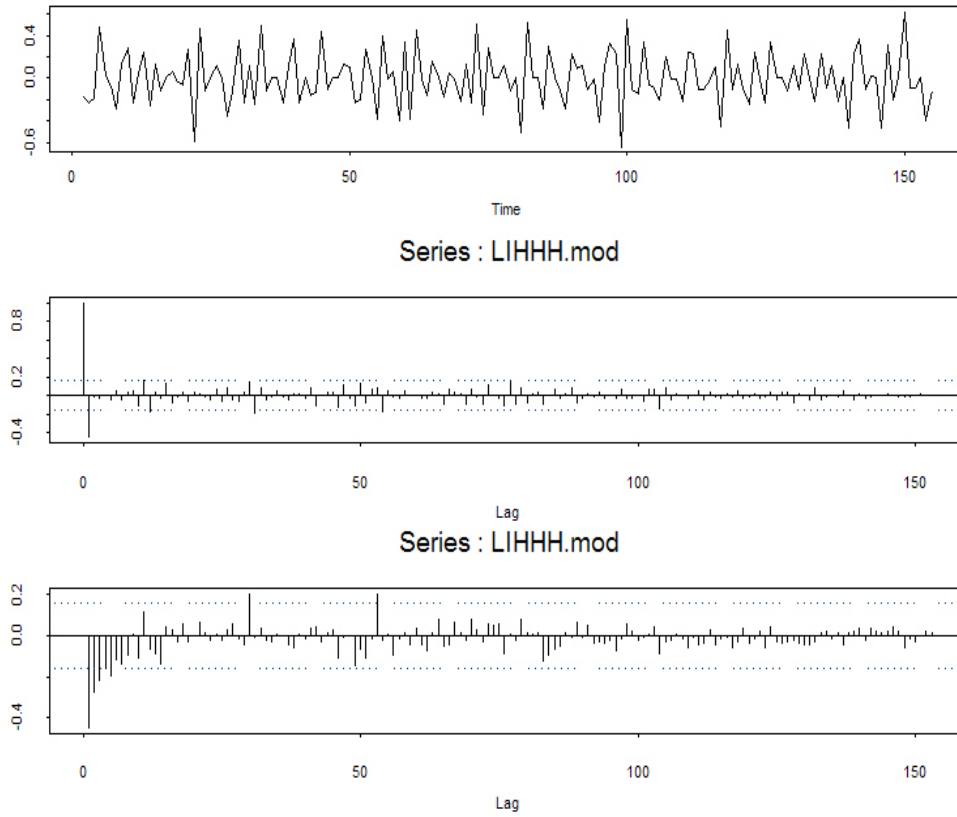


Figure 8 Differenced Time series plots of LIHHH

Model fitting by S-Plus yield coefficient MA = 0.9068 with lowest of AIC = -79.65. The residual diagnostics of ARIMA(0,1,1) reveal random residuals. The fitted LIHHH can be expressed as

$$x_t = x_{t-1} + \omega_t + 0.968\omega_{t-1} \quad (\text{Eq. 49})$$

where

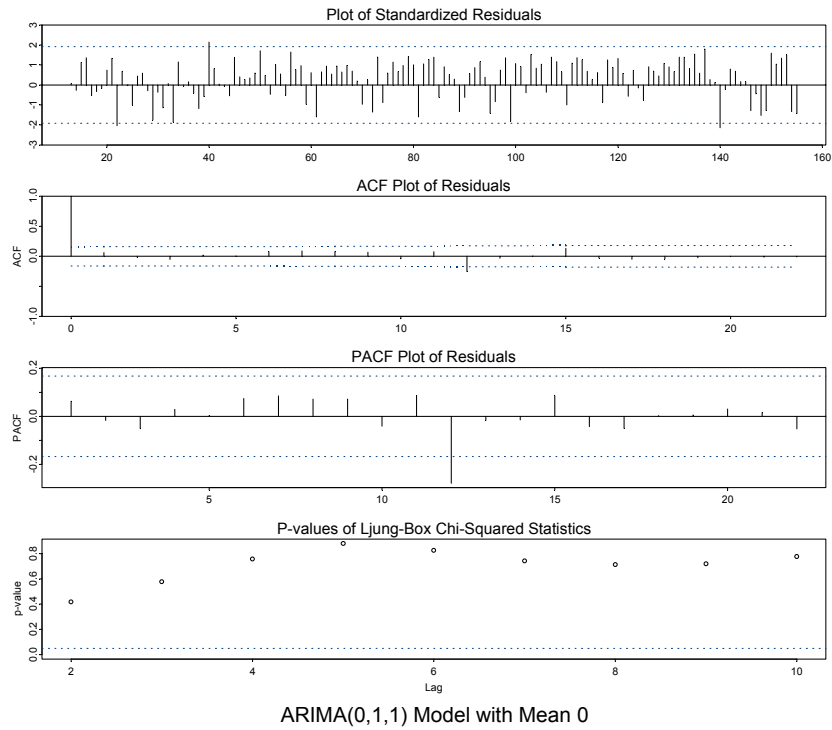
x_t = time series value at time t ,

x_{t-1} = time series value at time $t-1$,

ω_t = error value at time t ,

ω_{t-1} = error value at time $t-1$.

ARIMA Model Diagnostics: LIHHH



The seasonal fit of $ARIMA(0,1,1) \times (0,1,0)_{52}$ yield $AIC = 27.16$ which is greater than the $ARIMA(0,1,1)$ and therefore not recommended.

The remaining ARIMA model fitting graphs are shown in Appendix A. A summary of the ARIMA model fitting is shown in Table IX on the next page.

TABLE IX
SUMMARY ARIMA MODEL FITTING RESULTS

NO.	Name	ARIMA	AR	Diff	MA	AIC
1	LIHHH	(0,1,1)	0	1	0.9	-79.94
2	LIMHH	(0,1,1)	0	1	0.907	-79.66
3	LIHMH	(0,1,1)	0	1	0.93	-99.93
4	LIHHM	(0,1,1)	0	1	0.884	-182
5	LIMMH	(0,1,1)	0	1	0.933	-99.7
6	LIHMM	(0,1,1)	0	1	0.916	-207.6
7	LIMHM	(0,1,1)	0	1	0.879	-183.4
8	LIMMM	(0,1,1)	0	1	0.911	-208.4
9	LILHH	(0,1,1)	0	1	0.905	-79.36
10	LIHLH	(0,1,1)	0	1	0.958	-116.6
11	LIHHL	(0,1,1)	0	1	0.915	-32.78
12	LILLH	(0,1,1)	0	1	0.958	-116.3
13	LIHLL	(0,1,1)	0	1	0.966	-70.59
14	LILHL	(0,1,1)	0	1	0.914	-33.09
15	LILLL	(0,1,1)	0	1	0.965	-70.88
16	LILMM	(0,1,1)	0	1	0.916	-207.2
17	LIMLM	(0,1,1)	0	1	0.942	-230.1
18	LIMML	(0,1,1)	0	1	0.938	-58.22
19	LILLM	(0,1,1)	0	1	0.946	-229.4
20	LIMLL	(0,1,1)	0	1	0.966	-75.31
21	LILML	(0,1,1)	0	1	0.936	-53.61
22	LIHML	(0,1,1)	0	1	0.938	-53.33
23	LIMHL	(0,1,1)	0	1	0.916	-37.78
24	LILMH	(0,1,1)	0	1	0.929	-99.62
25	LIHLM	(0,1,1)	0	1	0.946	-229.8
26	LIMLH	(0,1,1)	0	1	0.959	-116.9
27	LILHM	(0,1,1)	0	1	0.886	-181.6

The ARIMA model fitting summarized in Table IX reveal that it is possible to fit the energy intensity index in a time series model. The results show that all the models are moving average (MA) models. Weather due to seasonal changes is not as significant when fitting the model as the trending from efficiency deterioration. In a more energy intensive process weather may play a more prominent role in the ARIMA model fitting and may require a seasonal model.

Discussion of Experimental Results

The experiments conducted for time series of the Refined Laspeyres energy intensity index and the Log Mean Divisia indexes with from the brick model over a 3 year period with 3 scenarios of product mixes, 3 scenarios of weather patterns, and 3 scenarios of system efficiency deteriorations accounts for 27 total scenarios. Time series plots of the Refined Laspeyres energy intensity index of 27 scenarios show the effects of the three main effects. Trending effects are very strong in the Log Mean Divisia index. The indexes increase rapidly in all 27 scenarios with increasing rate of amplitudes. This may be due to the logarithmic nature of the index and therefore is not recommended for use in long term monitoring.

The Refined Laspeyres energy intensity index is used to test for correlation with the influence of product mix. The results show that the intensity indexes are statistically correlated with the product mix and therefore can be used to monitor the “bare” energy intensity of the production process.

The intensity index time series can be used to develop ARIMA models. All 27 scenarios resulted in the recommendation of an ARIMA (0,1,1) model which is an Integrated Moving Average model. None of the weather impacts were significant enough to include in the seasonal ARIMA model, ARIMA (p,d,q)x(P,D,Q)⁵².

CHAPTER VIII

SUMMARY, DISCUSSIONS, AND RECOMMENDATIONS

8.1 Introduction

From Chapter 7, statistical test results indicated that the Refined Laspeyres energy intensity index is the more suitable to use as a plant-level energy monitoring index than Log Mean Divisia because of the consistency in responding to changes and not amplify the changes over time. The results also show that Refined Laspeyres energy intensity index has no correlation with the production mix. In other words, the energy intensity index is not influenced by changes in product mix.

This chapter presents the major contributions and the usefulness of this research. This chapter also includes the strength and limitations of the techniques and the use of energy intensity index. Finally, the chapter explores opportunities to improve the technique and future development of this research.

8.2 Major Contribution of This Research

In industrial settings, one of the challenges energy managers encounter when performing monitoring on the facility's energy usage is the influence of changes in product mix, production quantity, and weather impact. These factors influence the energy usage in the plant and mask the "bare" production energy efficiency. This research introduces a procedure to un-mask the bare production energy efficiency by incorporating the use of

energy intensity index as a tool to monitor the changes in energy consumption. The intensity index uses energy intensity, kJ/kg, as a part of calculation which eliminates the production quantity mask. Further statistical tests showed that the Refined Laspeyres intensity index is not influenced by the changes in product mix. These benefits provide energy engineers with better knowledge of the facility's production efficiency. The research results also indicate that the intensity index can be fitted into an ARIMA model which is one of the most used models in forecasting. Energy managers can use this model to monitor the current facility production efficiency changes. In addition, since ARIMA models are one of the most powerful models used to better understand the data or used for prediction, engineers can use these models to plan for future recommissioning effort by applying forecasting techniques. The increasing in energy intensity (trend) and erratic energy intensity behavior can help engineers understand the healthiness of the process and able to project on when improvements are needed.

8.3 Strengths and Limitations

From the experimental results, the advantage of the use of energy intensity index as an alternative production energy efficiency monitoring technique is that the index is not influenced by the changes in product type.

The model tested was on weekly data over a three years period. After fitting the ARIMA model, the weather impact was recognized as a part of general white noise (residual). Researchers wishing to continue this study need to recognize the weather impact and also test for seasonality of the model in the time series fitting. More complex models may be used should the weather plays an important role. An example of more complex model include but not limited to SRIMA or $ARIMA(p,d,q) \times (P,D,Q)$.

The study was performed on a flow shop environment, the modeled facility was not air conditioned. In other production type environments for example, a facility with air conditioning and complex production lines, more complex data gathering processes may be required, for example sub-metering of multiple furnaces, motors, and the production

lines. For thermally heavy processes including air conditioning, the author speculates that additional air conditioning sub-metering may be required.

The indexes used in this research are assumed to be intensity index (energy used per unit of production) not value based. Researchers can later convert to currency-based intensity indexes (dollars of energy per unit of production) to justify the future forecasting for a recommissioning project.

8.4 Future Research

There are opportunities for expansion of this research

1. Index decomposition methodology mainly composed of Intensity index, Production Mix index, and Production Quantity index (please refer to Chapter 2). This research explores the energy intensity index. As an overall facility well-being, the product mix and production quantity (production index) can be further explored in similar way.
2. Use other types of trend signals. This research explored the linear decay of the overall efficiency over a long term period of 3 years. Further studies are needed to explore other types of decay signals. This may also include actual data gathering over a long term period from the time when major energy conservation efforts have been implemented.
3. The expanded universe of the plant-level energy intensity index monitoring is to develop forecasting processes to plan for future re-commissioning. Since this research uses ARIMA models as a standardized model of the indexes, it can be expanded into forecasting.
4. Short term (one year) monitoring with LMDI. From the results in Chapter 7, the Log Mean Divisia energy intensity index resulted in large variation when used over a long term period. The high sensitivity of this index can be explored to consider its use used as a short term energy monitoring technique.

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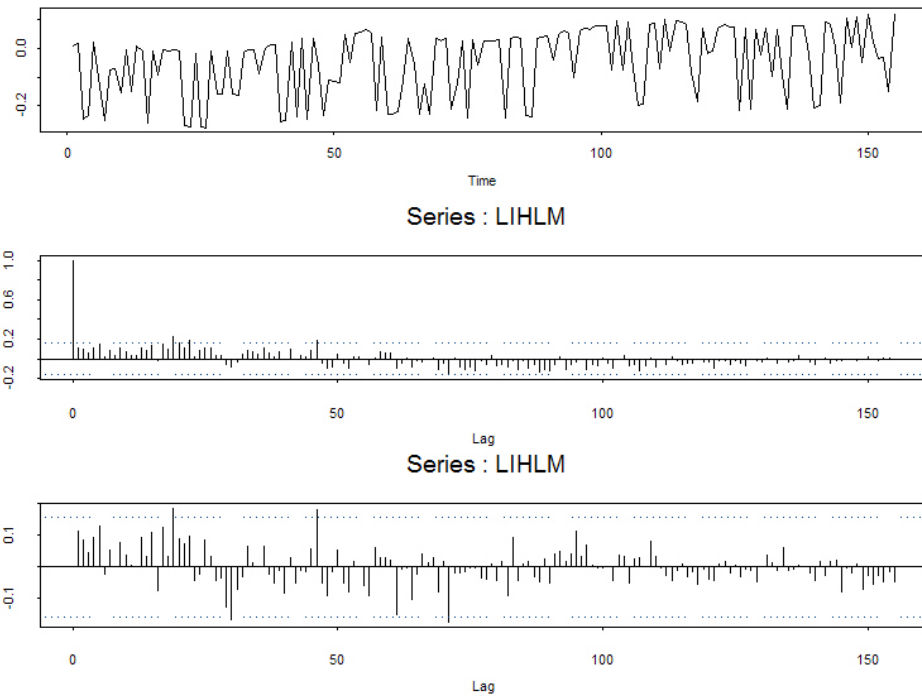
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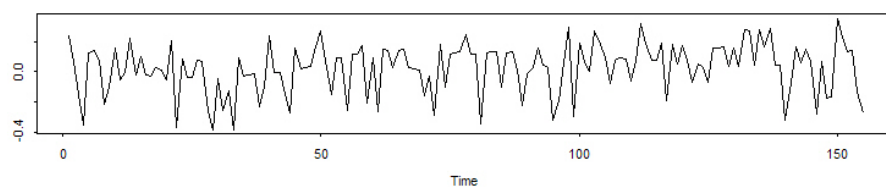
APPENDIXES

APPENDIX A: GRAPH OF SIMULATION RESULTS

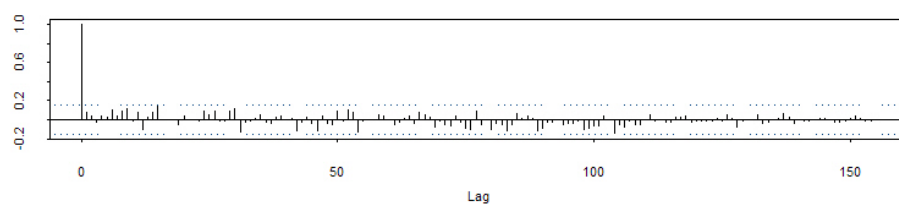
Refined Laspayres Energy Intensity Index

1. Time series of Refined Laspayres Energy Intensity Index (Top)
2. Auto Correlation of Refined Laspayres Energy Intensity Index (Middle)
3. Partial Refined Laspayres Energy Intensity Index (Bottom)

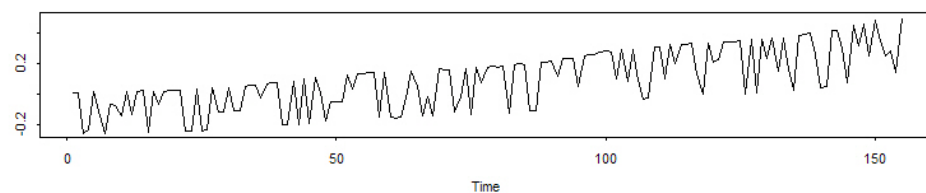
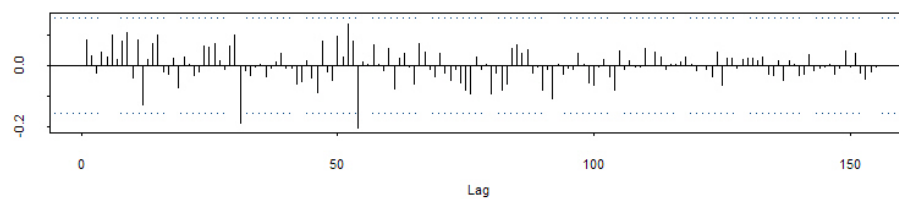




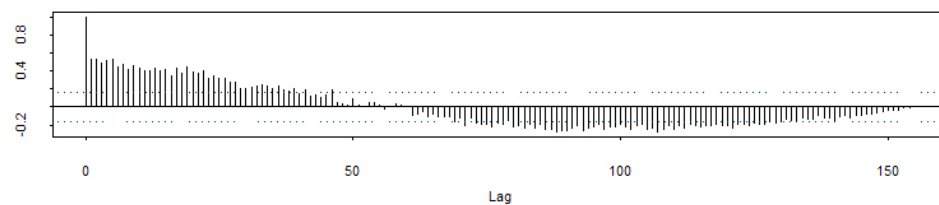
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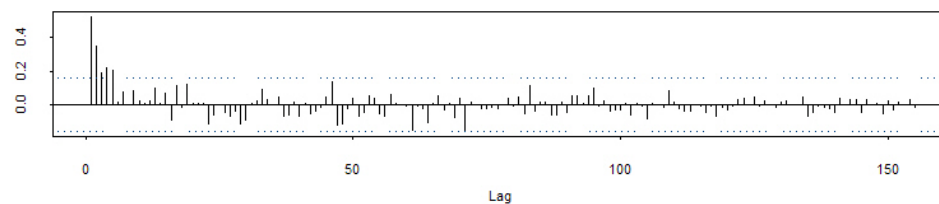
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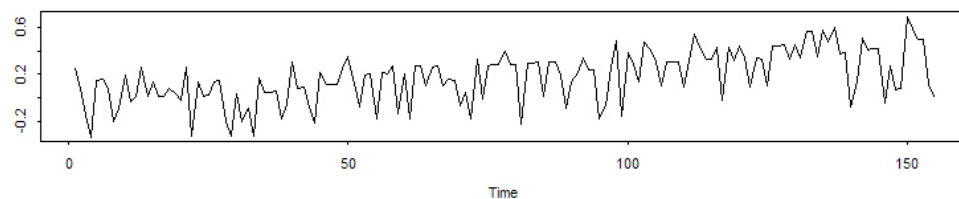


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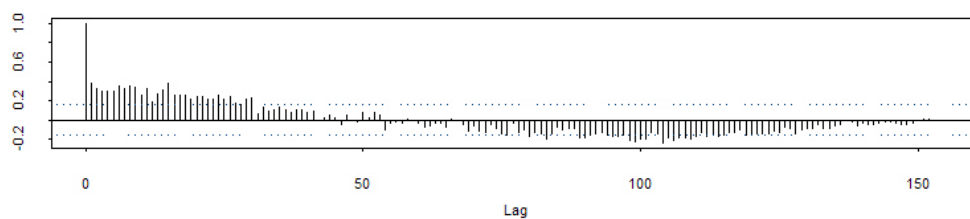


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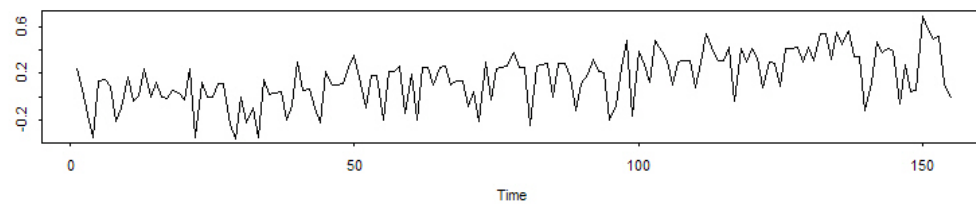
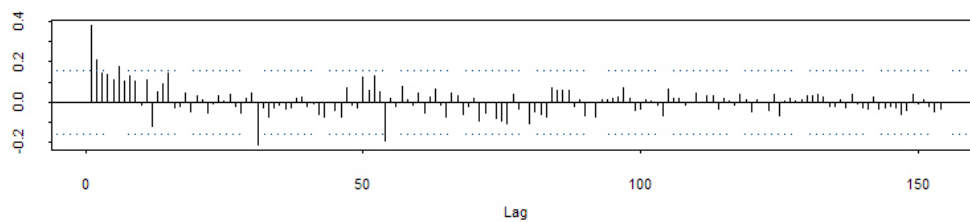




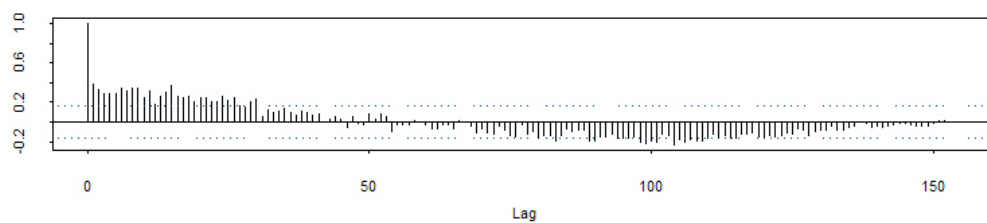
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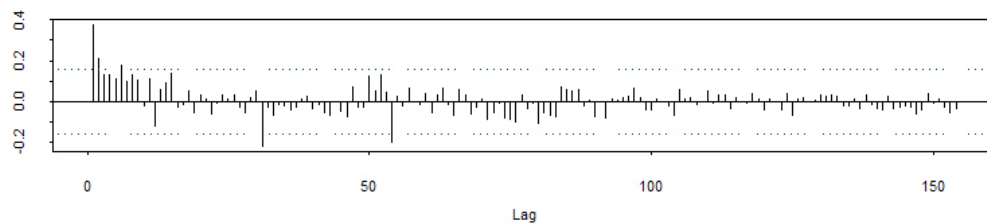
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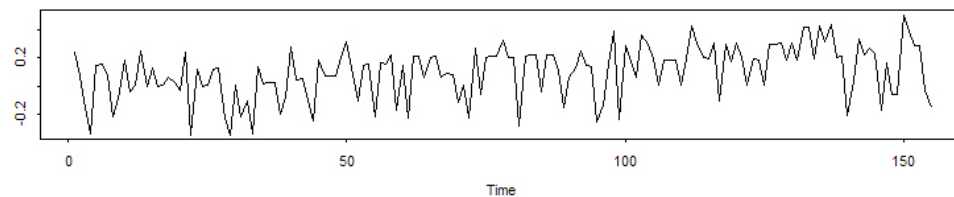


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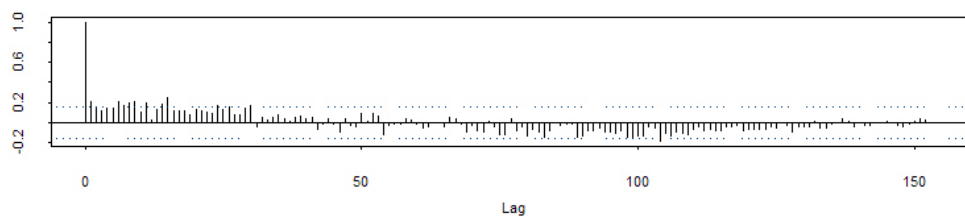


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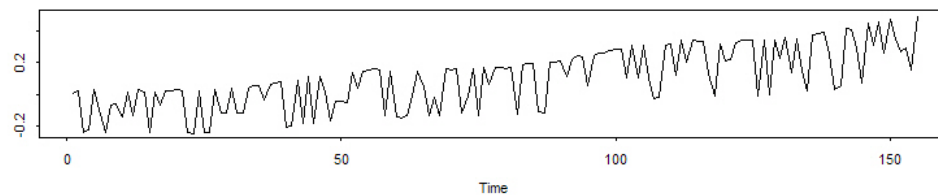
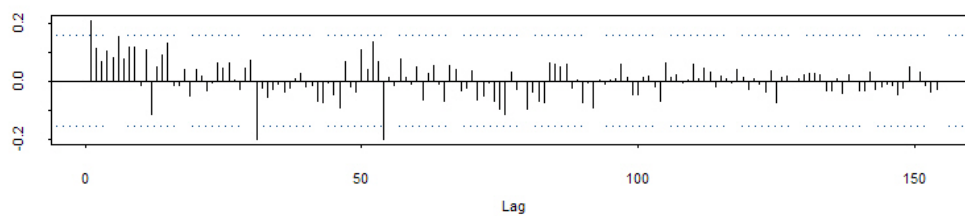




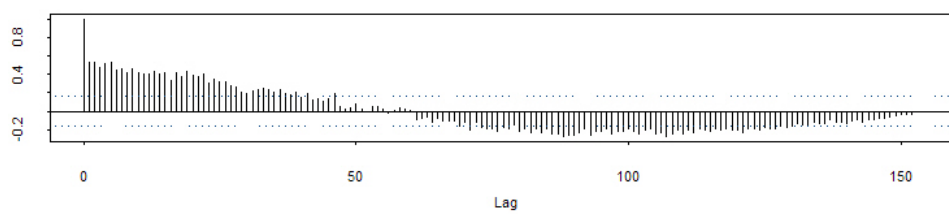
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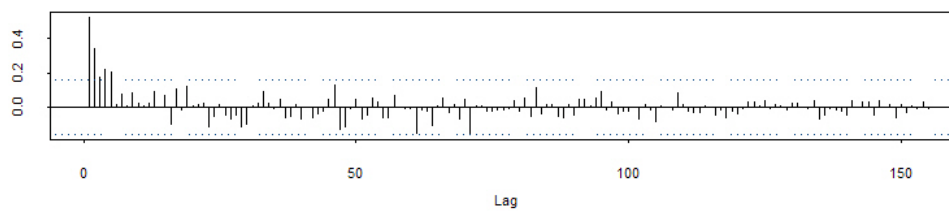
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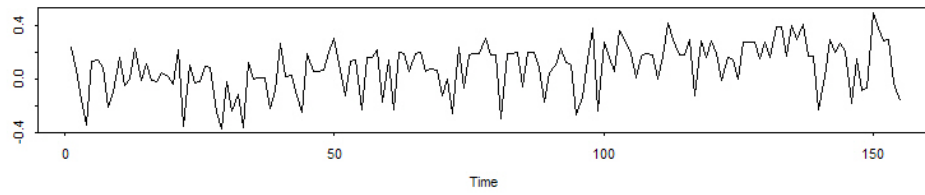


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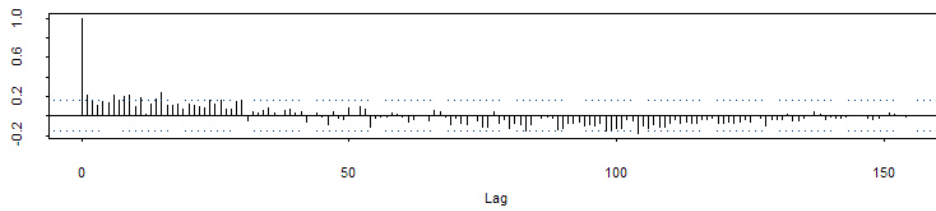


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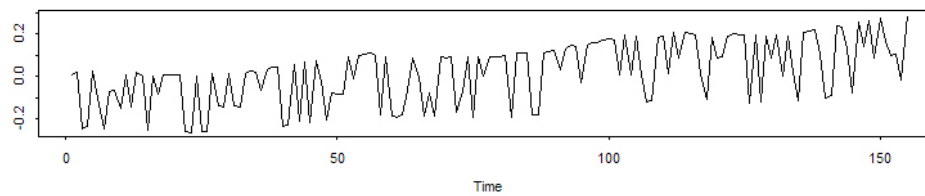
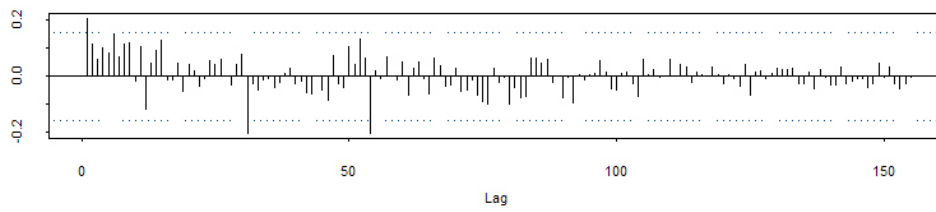




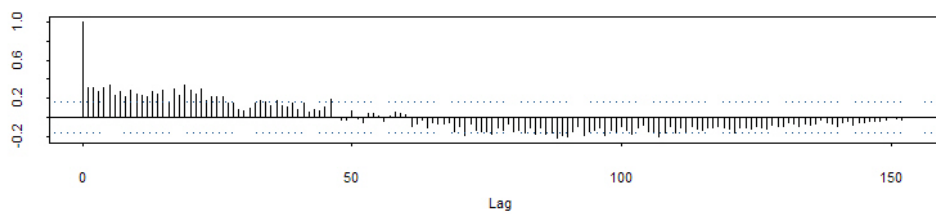
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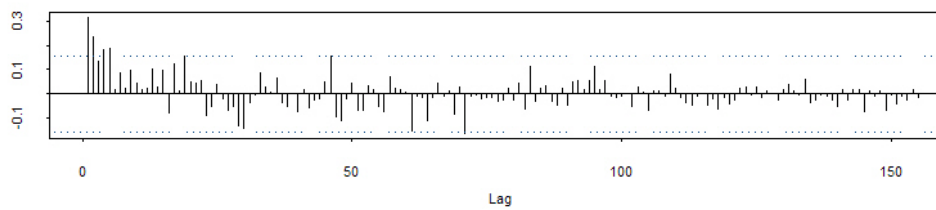
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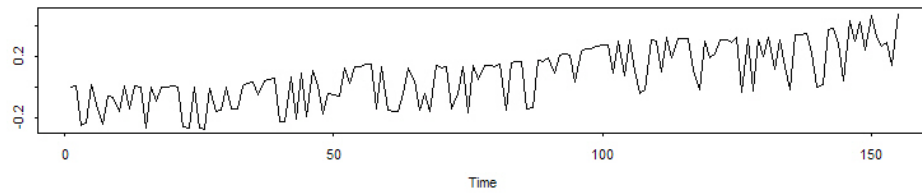


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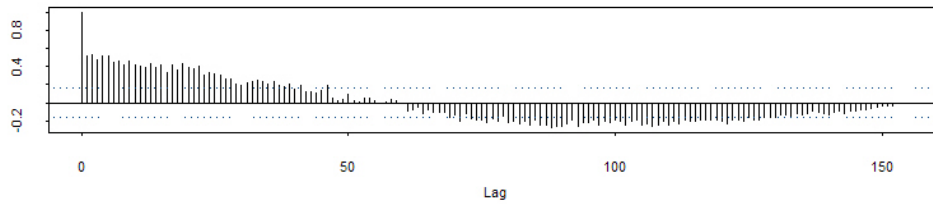


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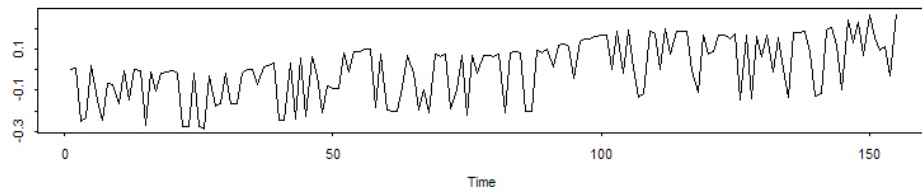
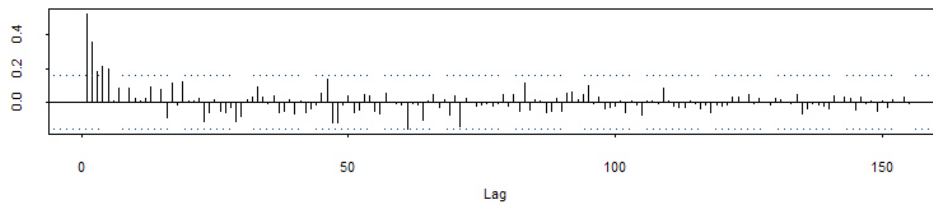




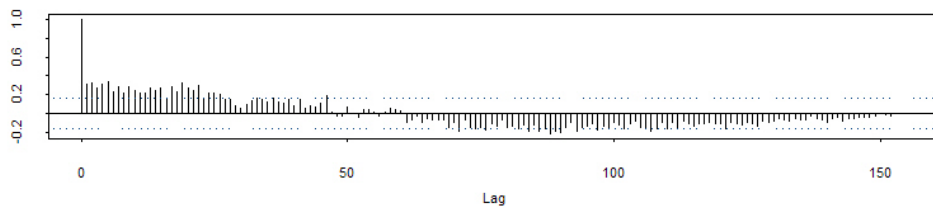
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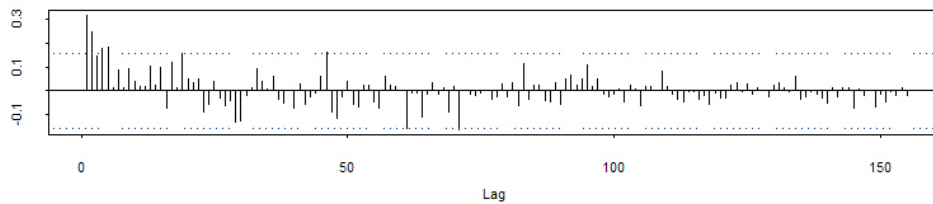
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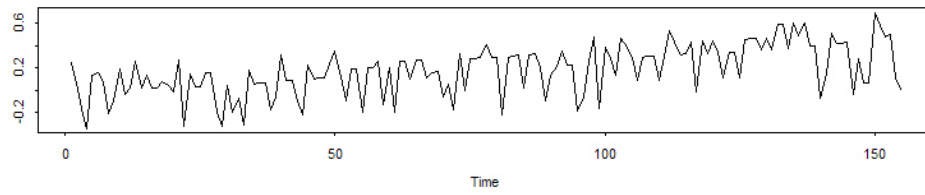


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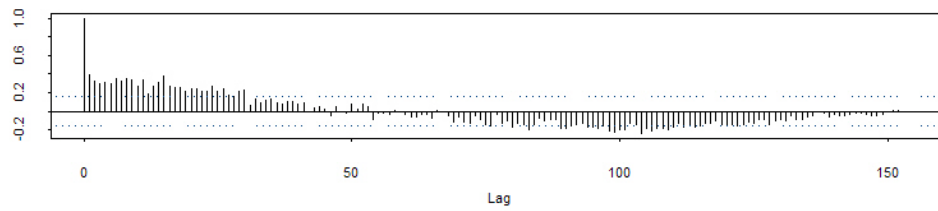


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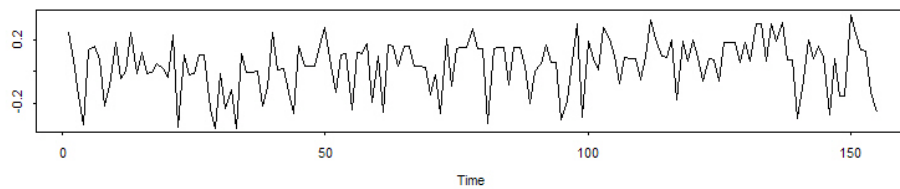
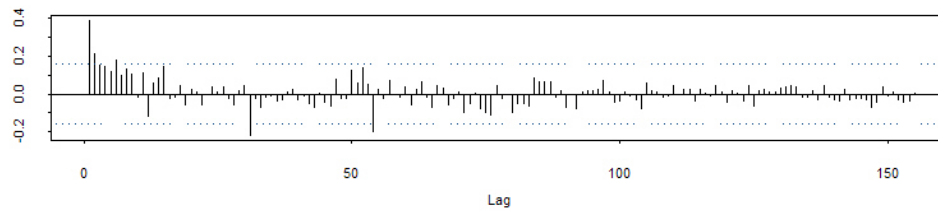




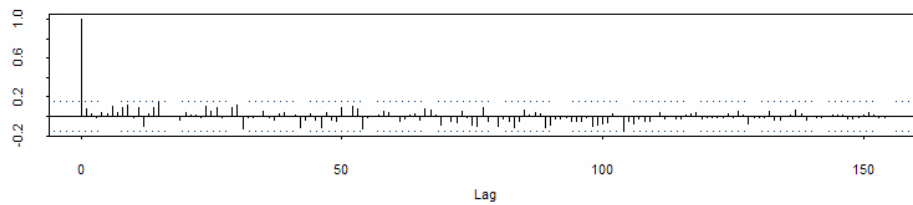
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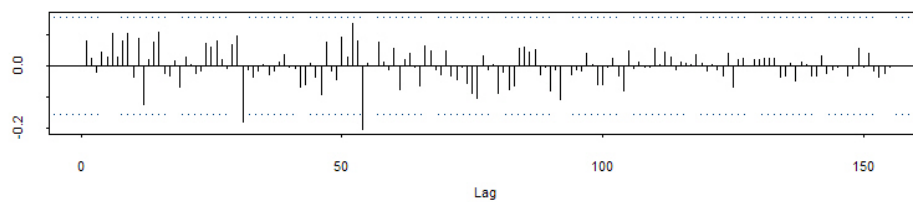
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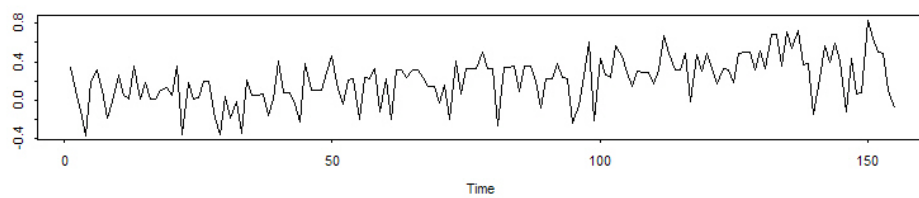


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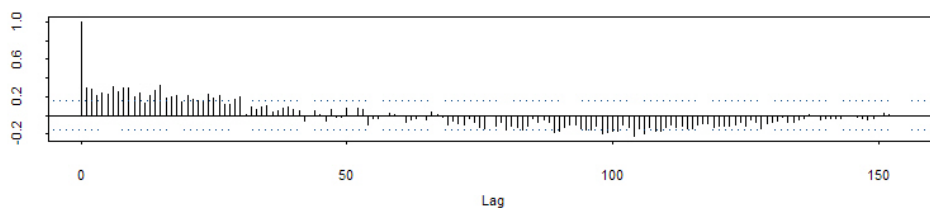


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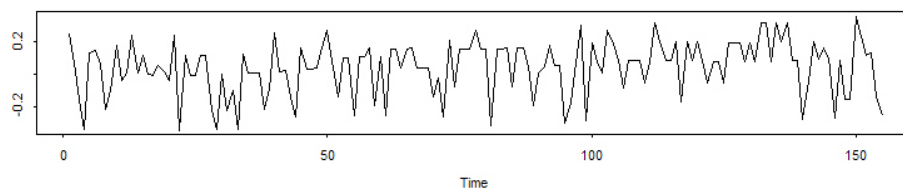
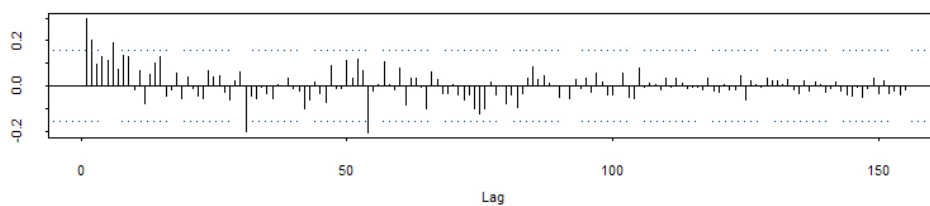




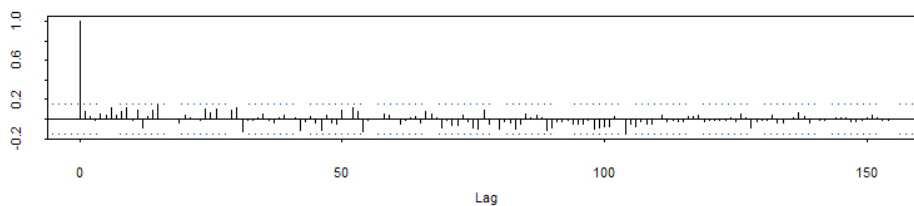
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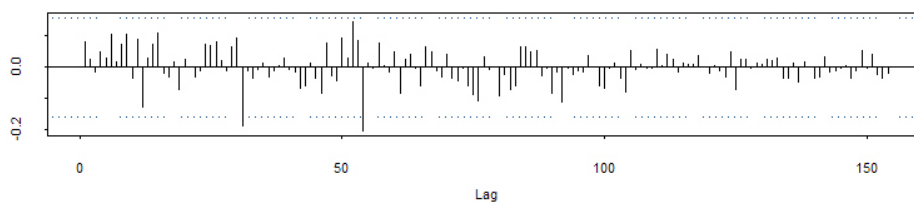
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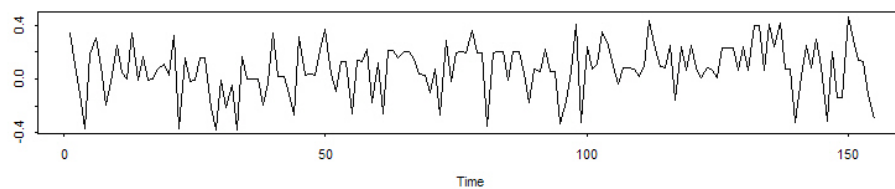


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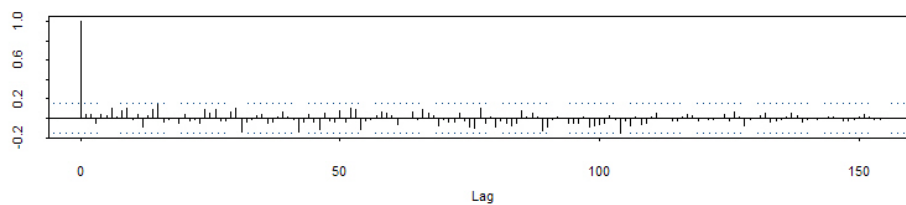


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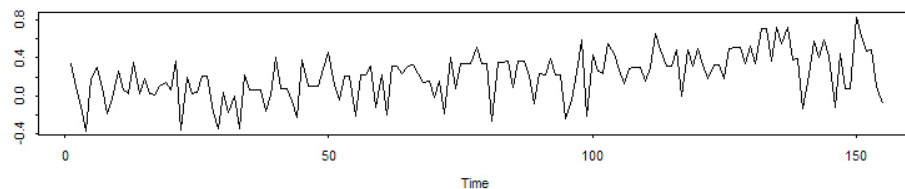
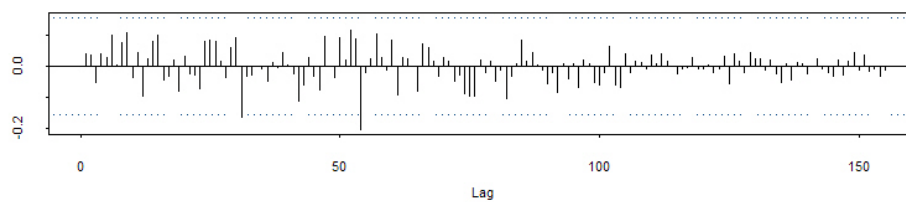




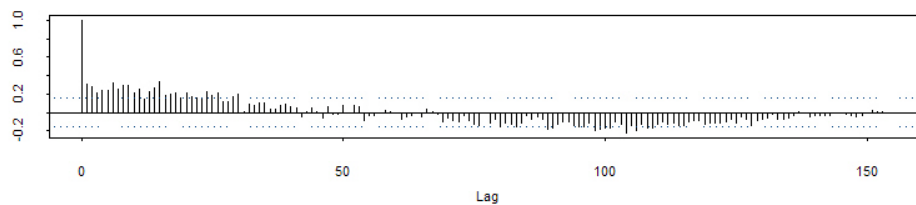
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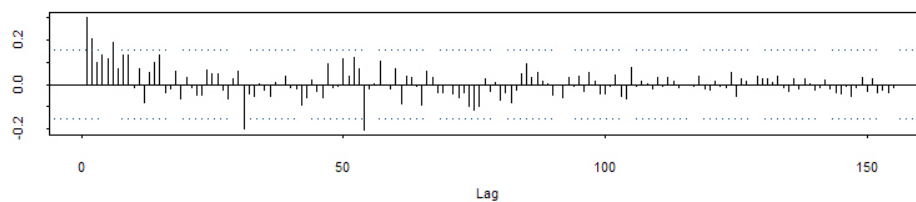
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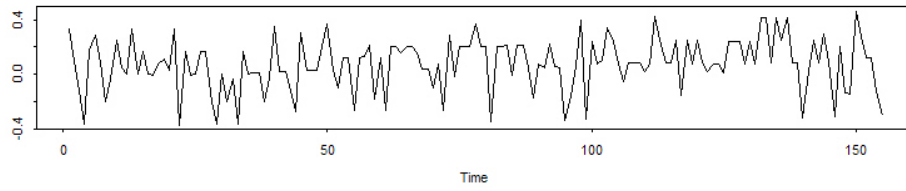


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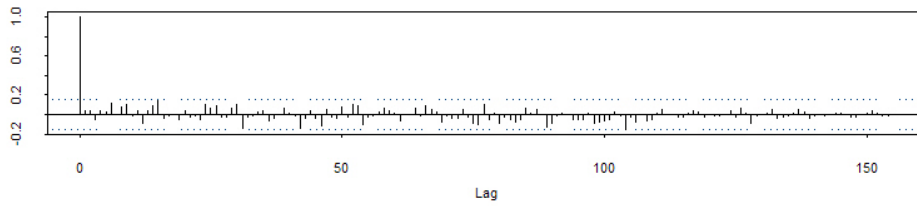


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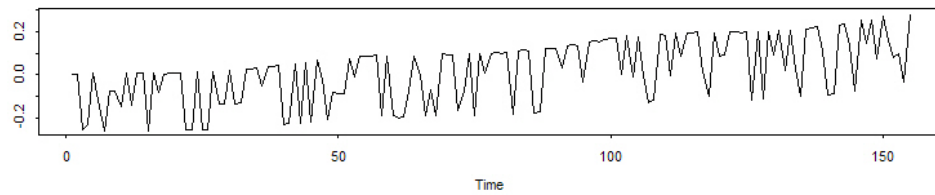
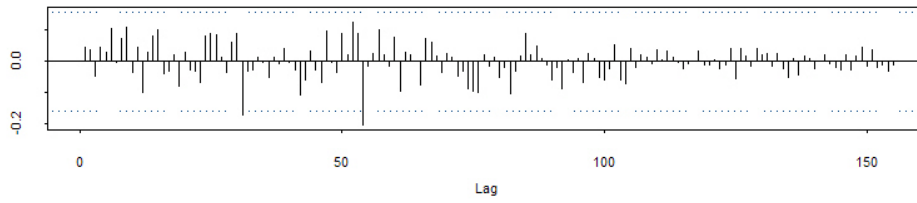




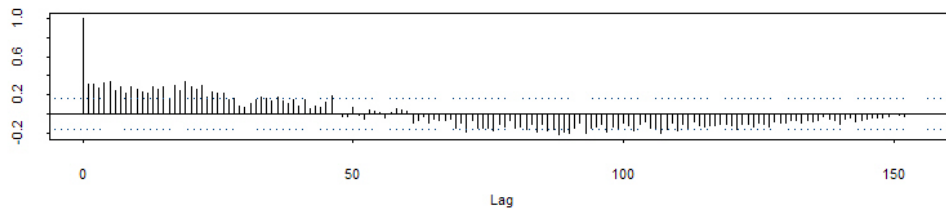
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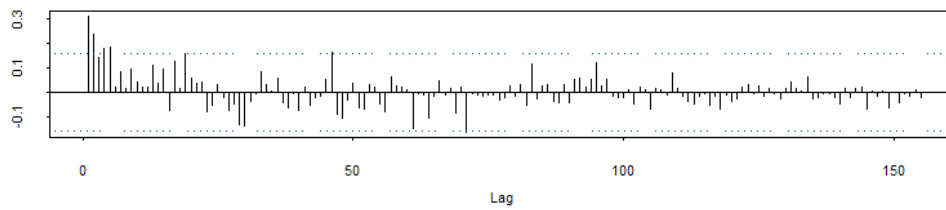
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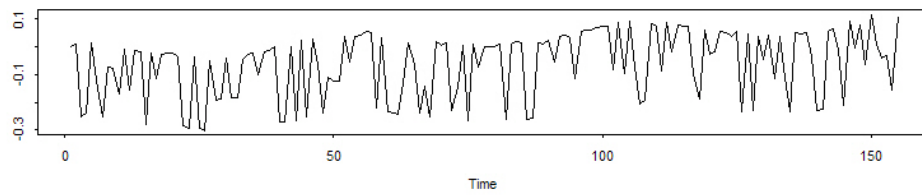


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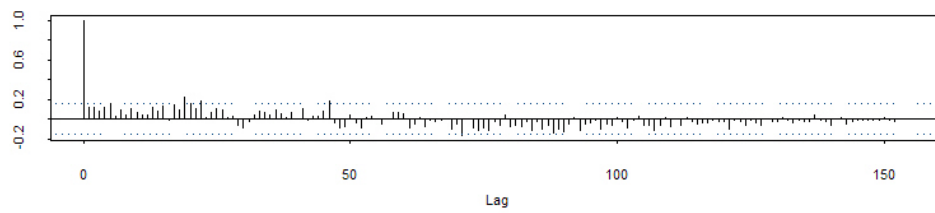


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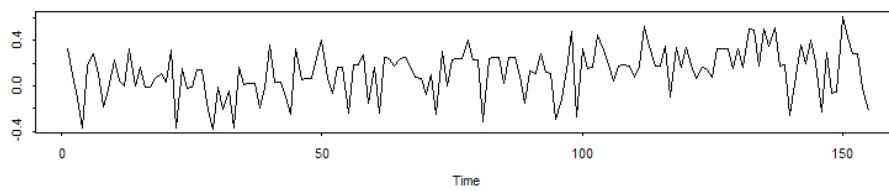
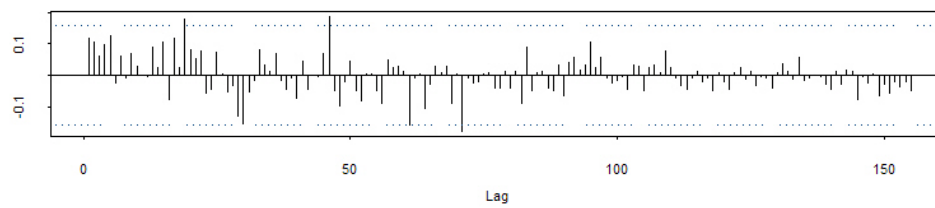




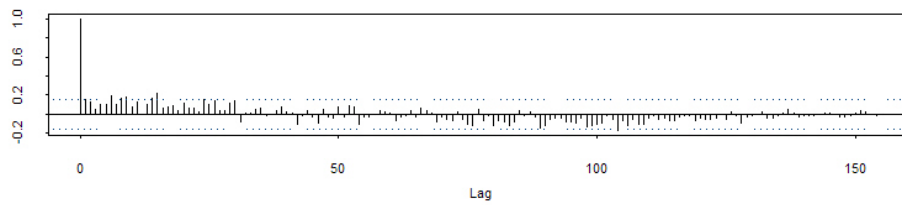
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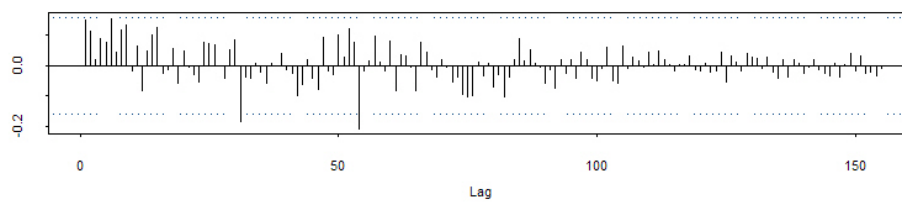
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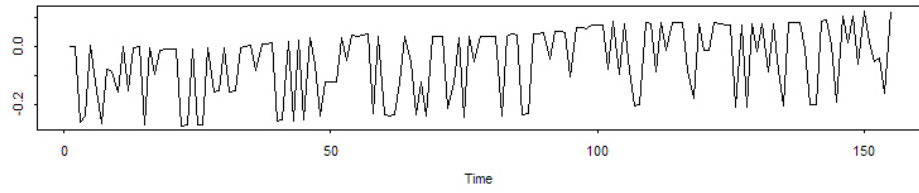


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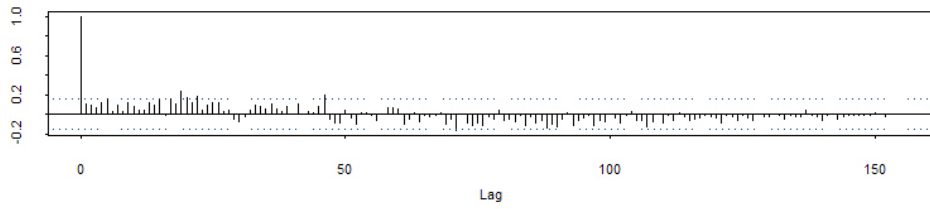


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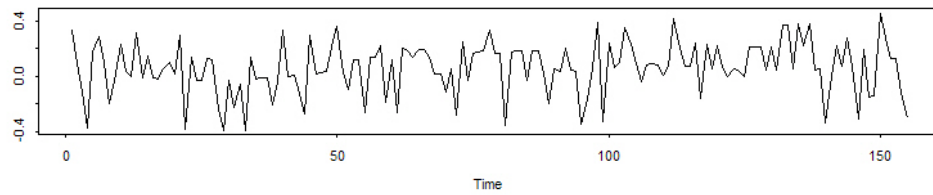
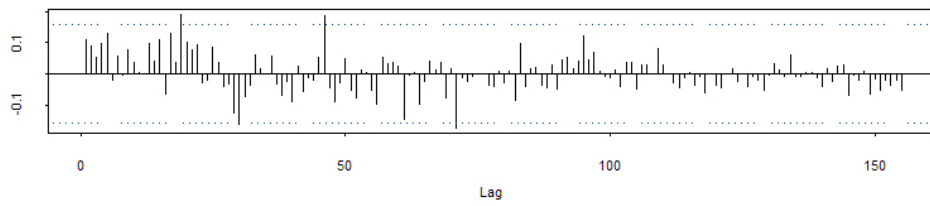




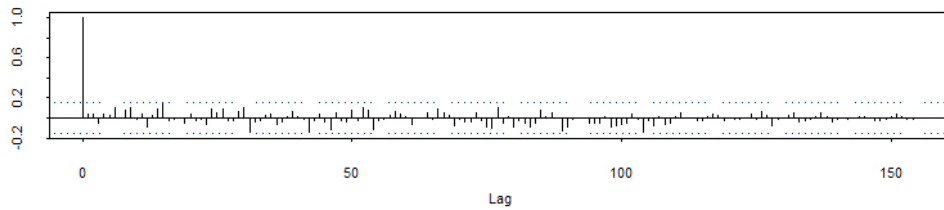
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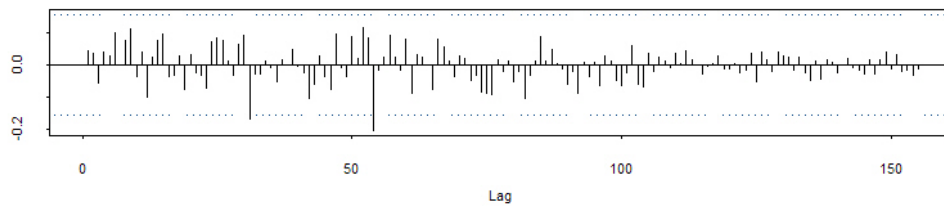
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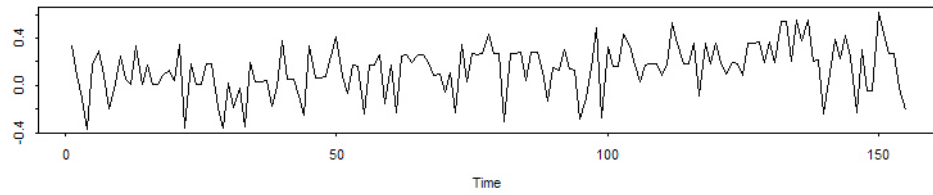


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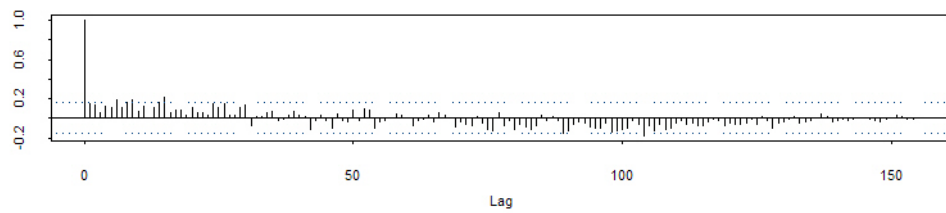


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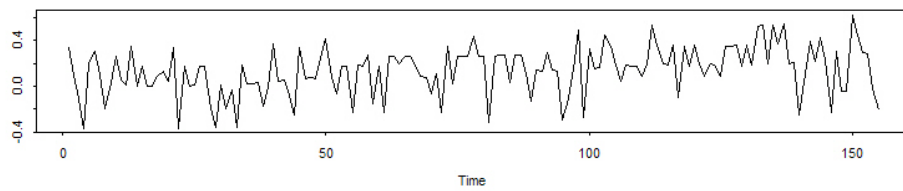
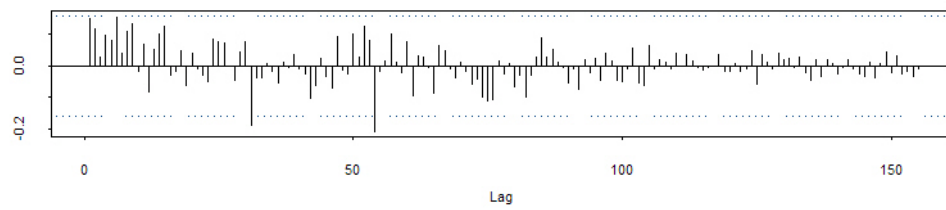




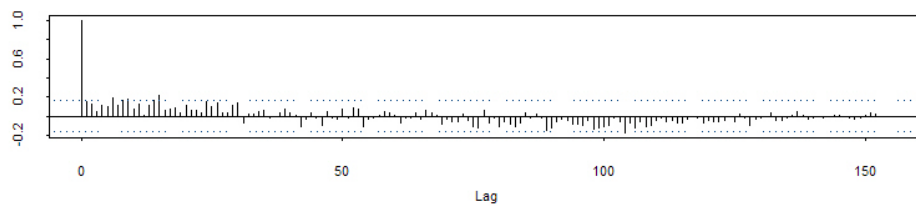
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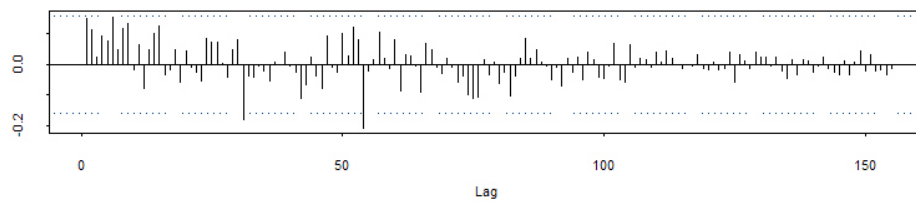
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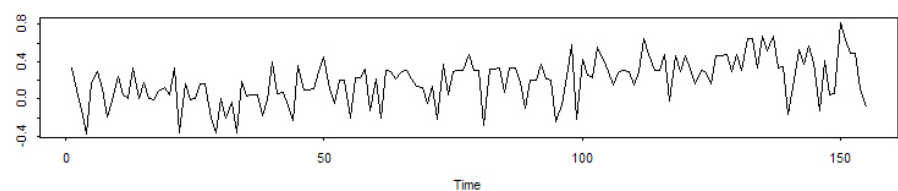


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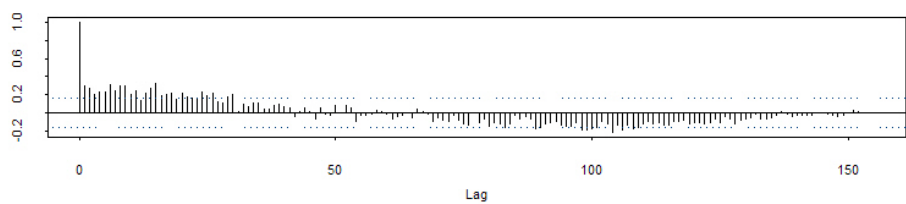


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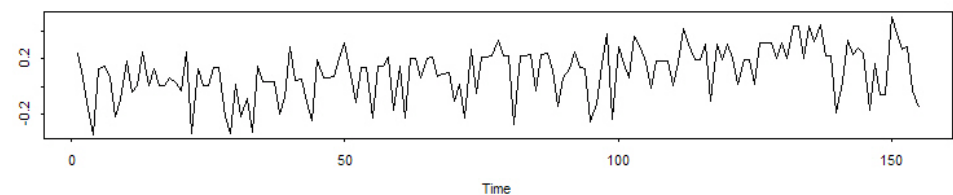
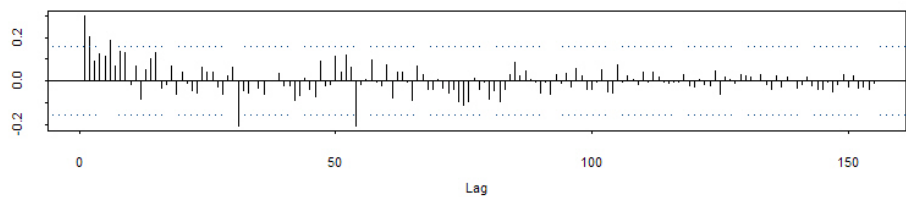




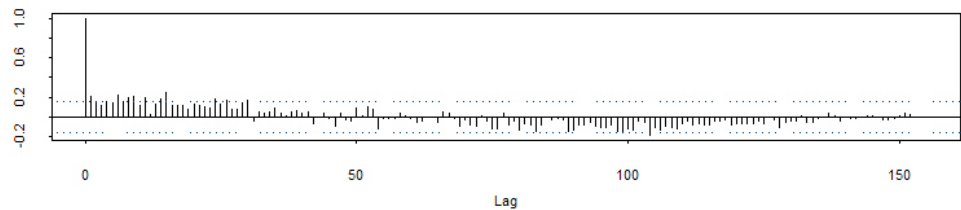
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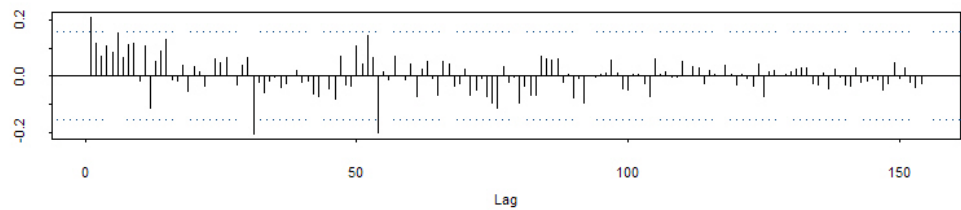
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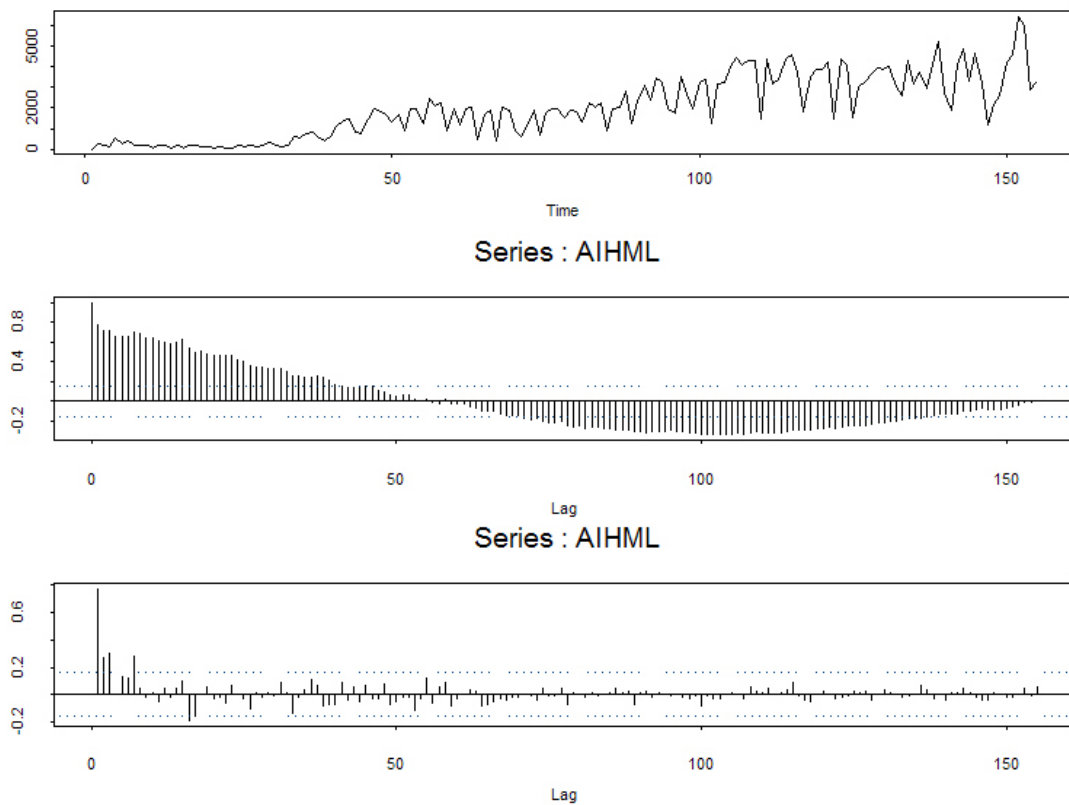


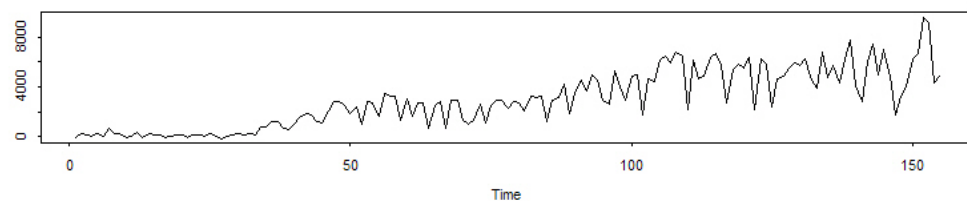
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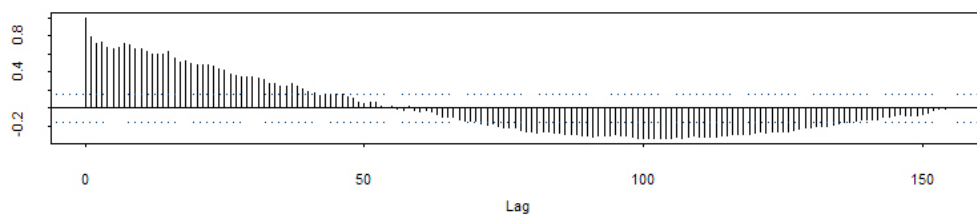
Log Mean Divisia Energy Intensity Index

4. Time series of Log Mean Energy Intensity Index (Top)
5. Auto Correlation of Log Mean Energy Intensity Index (Middle)
6. Partial Refined Log Mean Energy Intensity Index (Bottom)

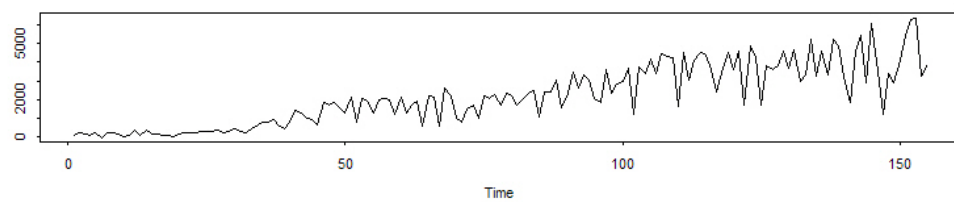
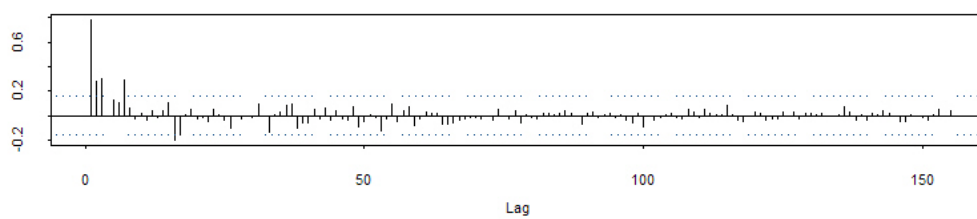




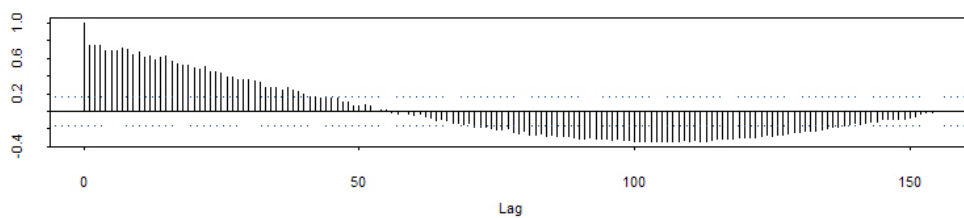
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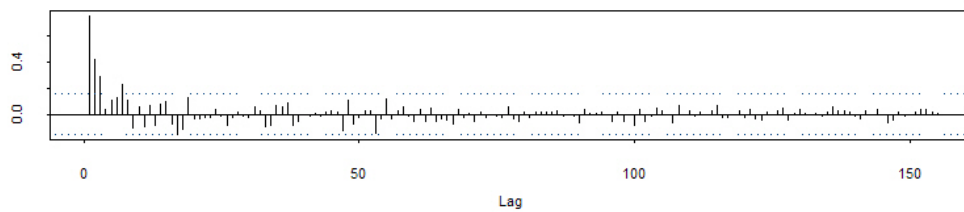
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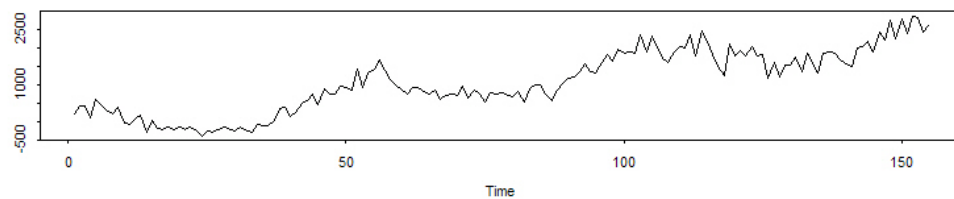


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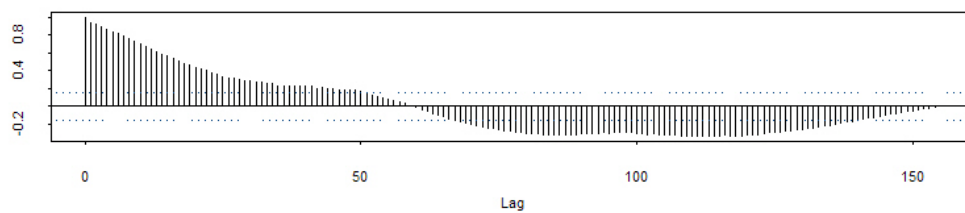


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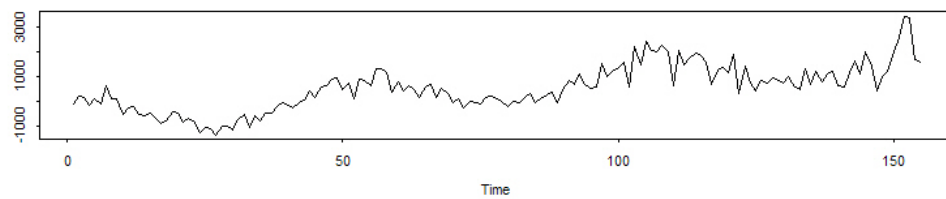
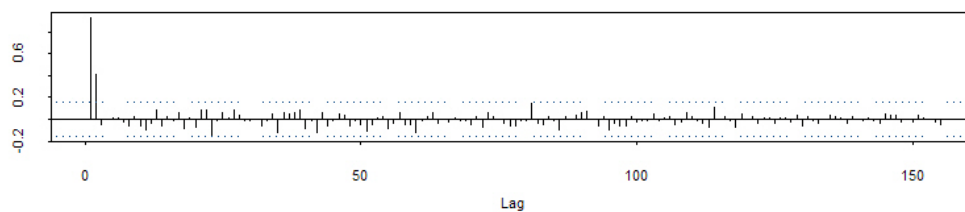




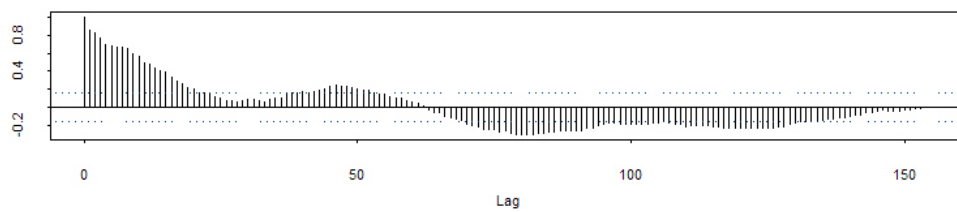
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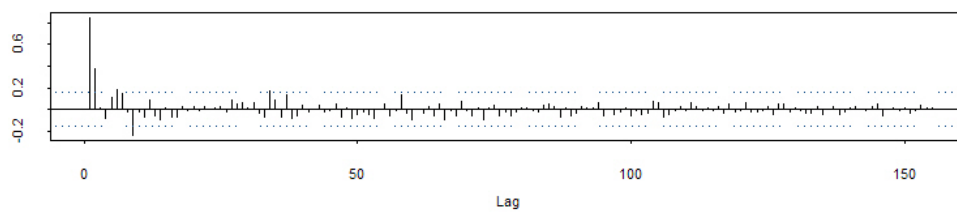
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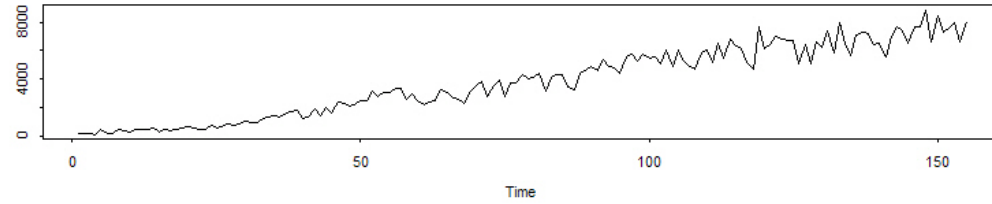


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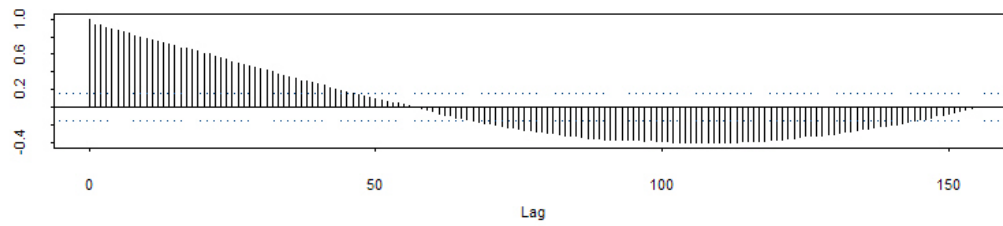


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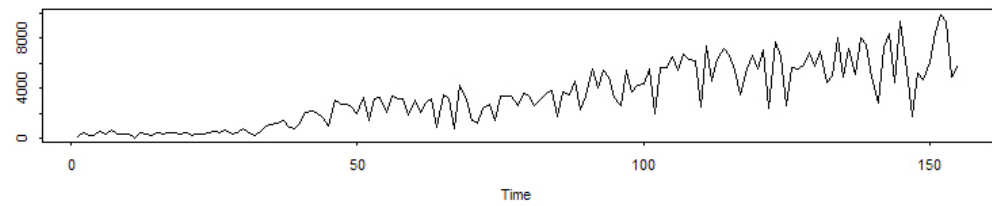
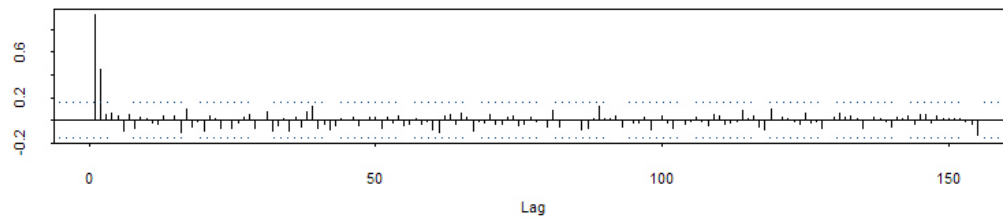




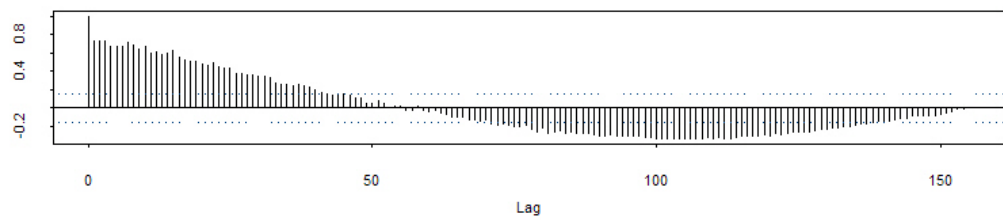
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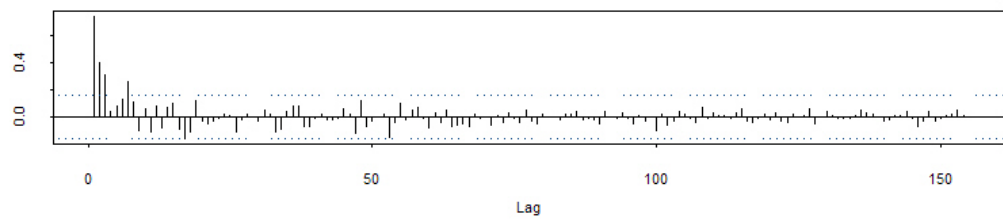
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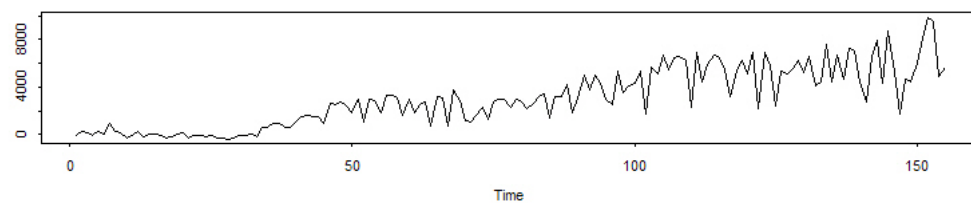


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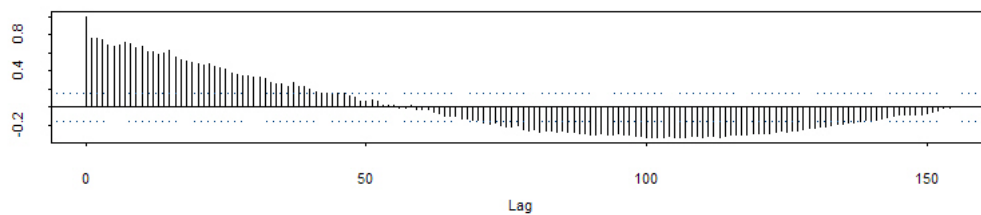


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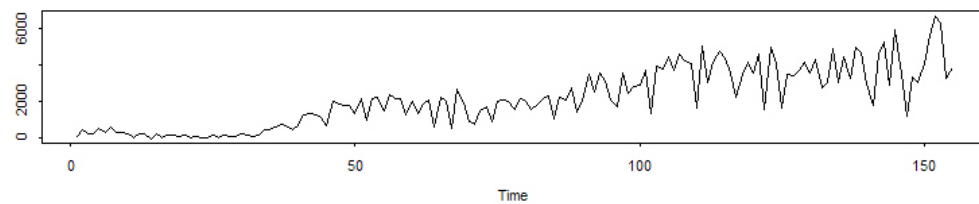
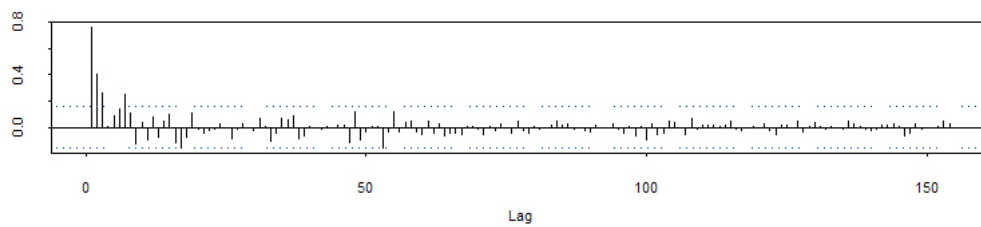




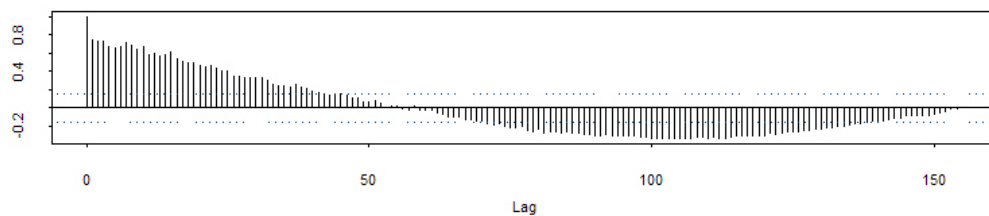
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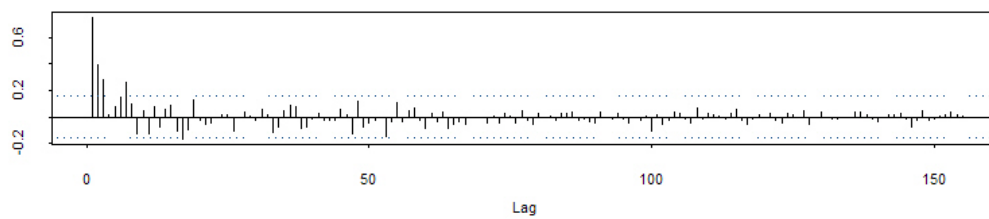
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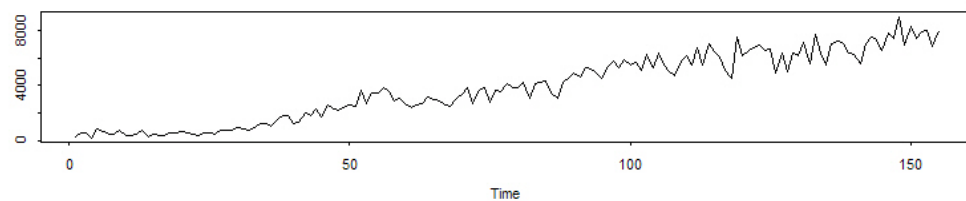


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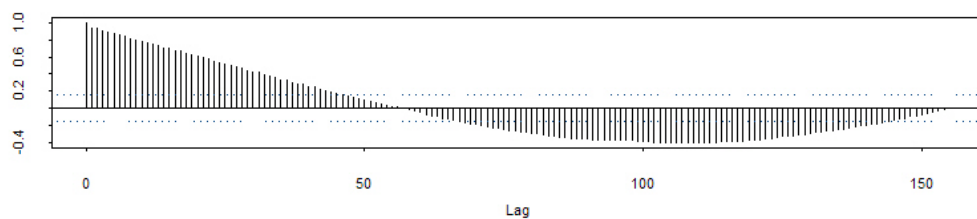


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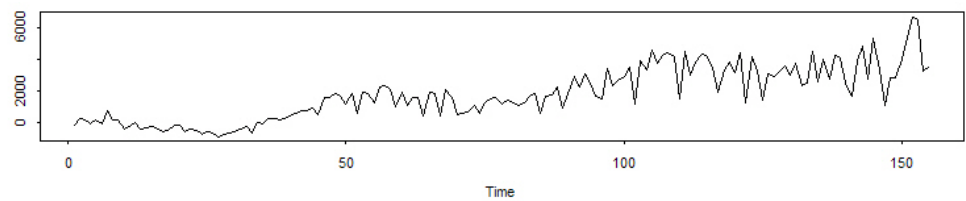
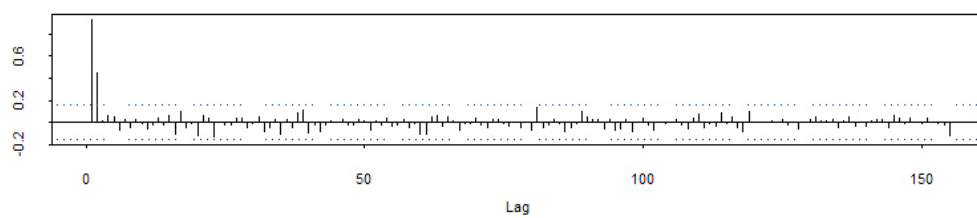




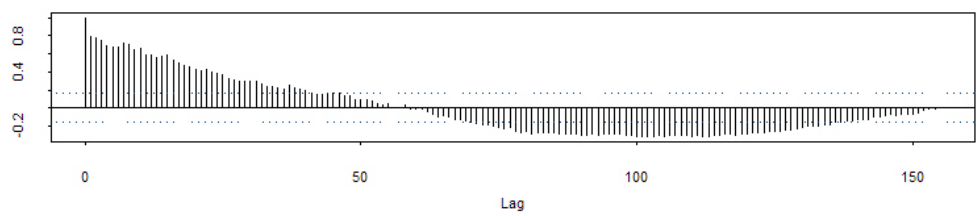
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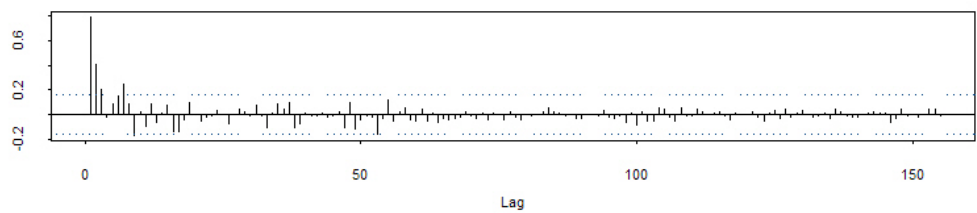
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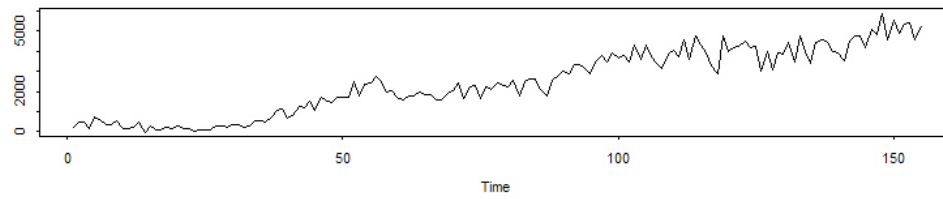


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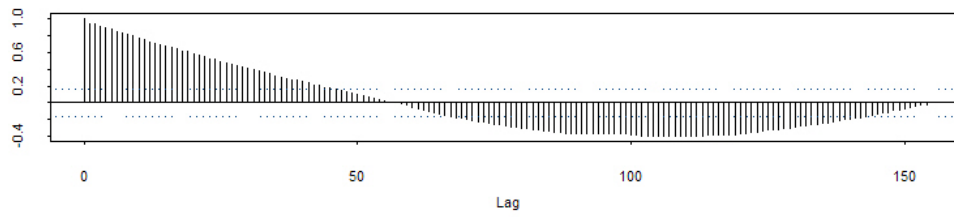


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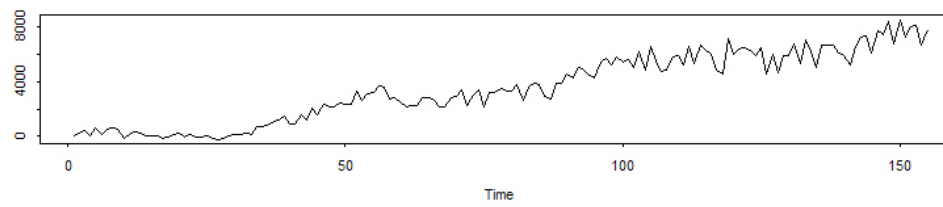
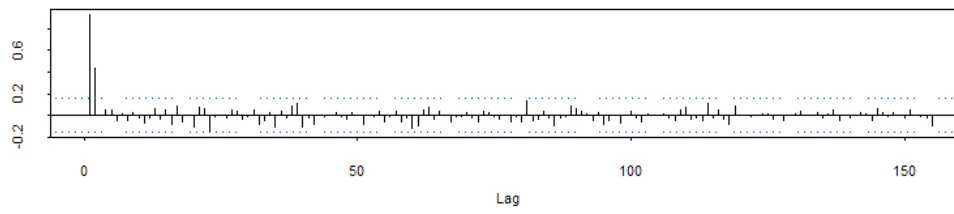




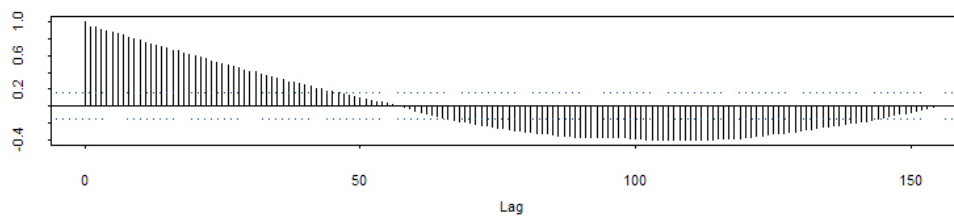
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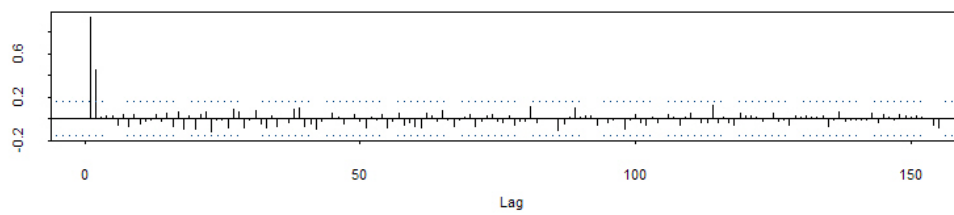
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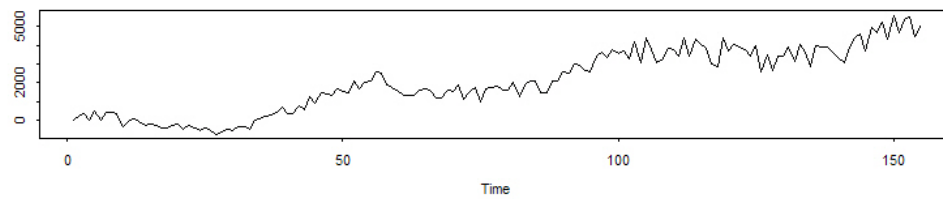


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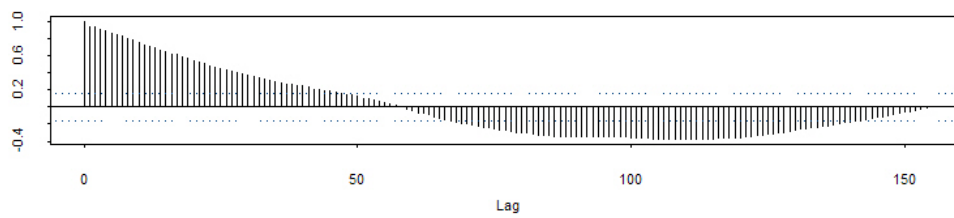


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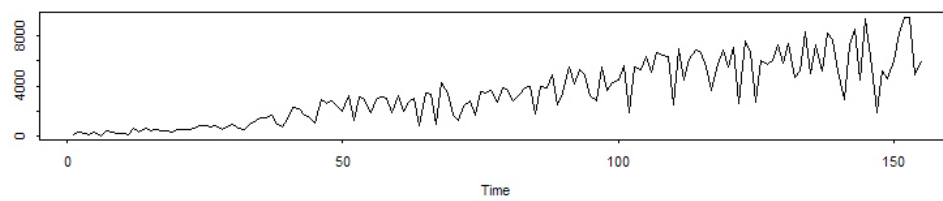
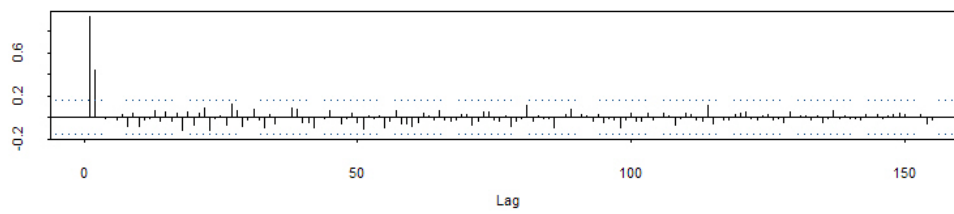




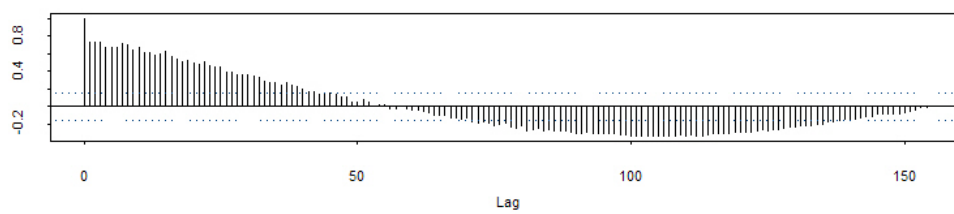
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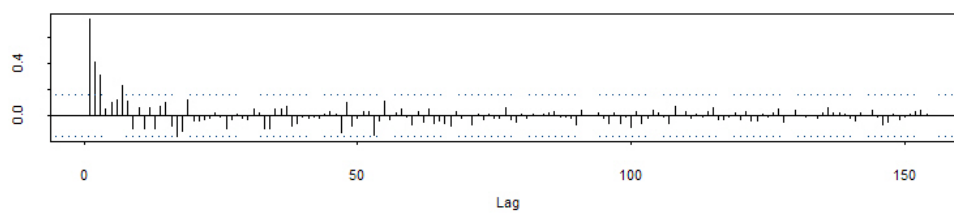
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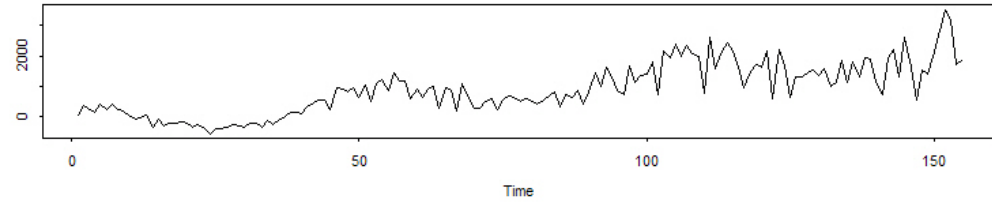


Series : AILHH

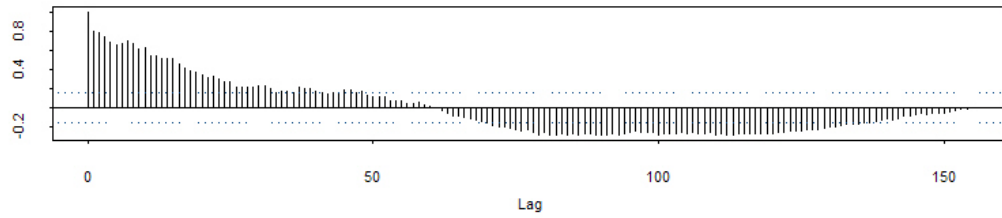


Series : AILHH

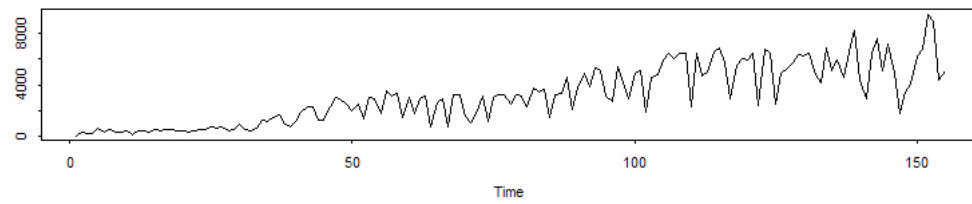
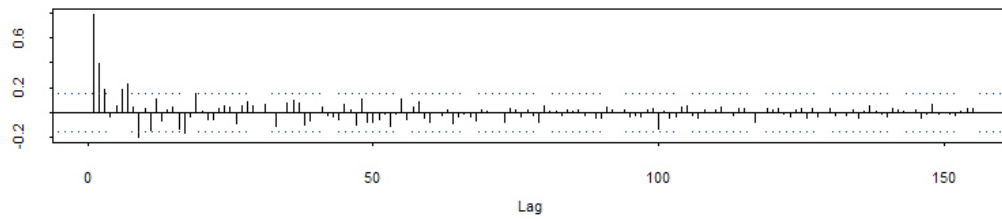




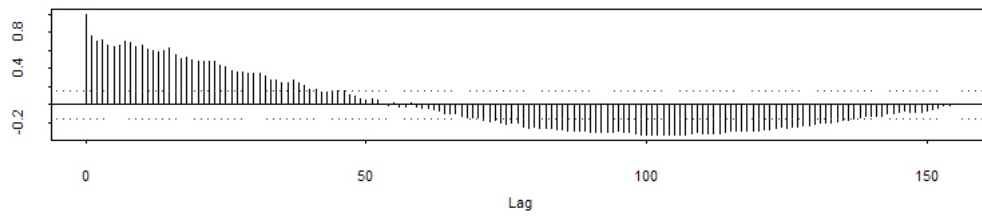
Series : AIHLH



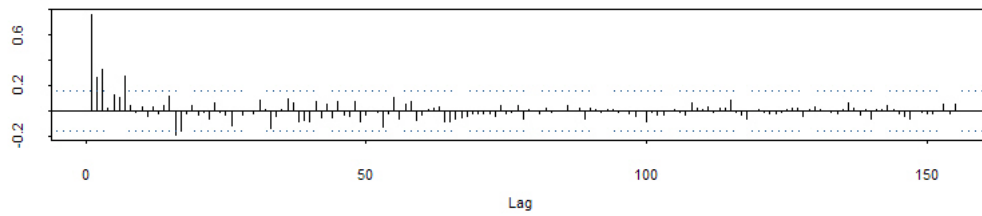
Series : AIHLH

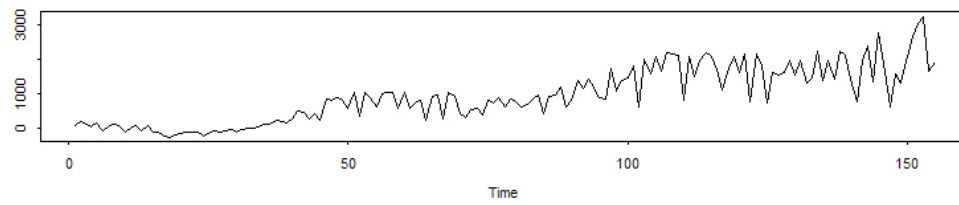


Series : AIHHL

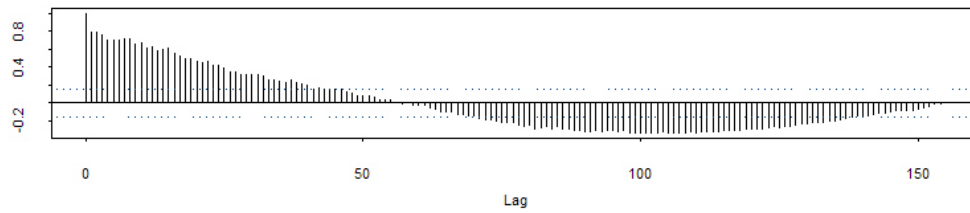


Series : AIHHL

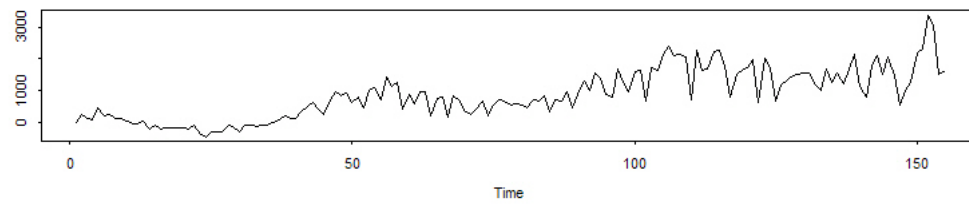
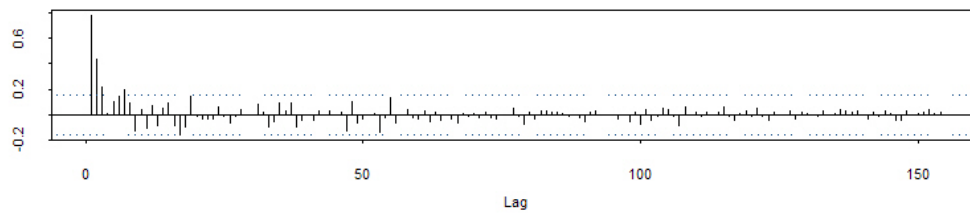




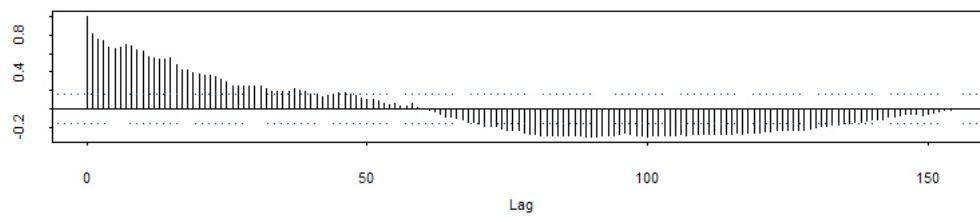
Series : AILLH



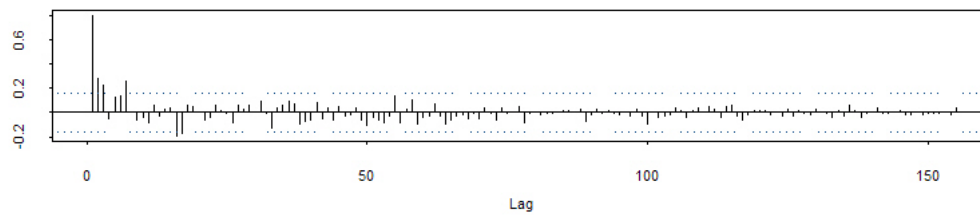
Series : AILLH

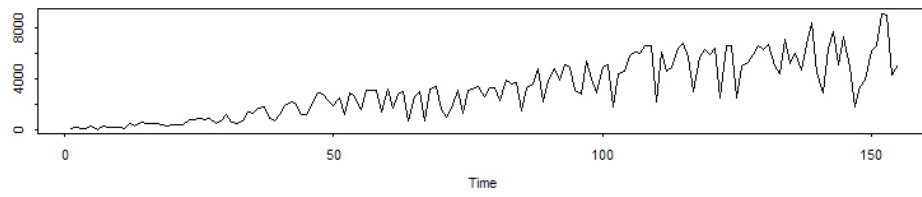


Series : AIHLL

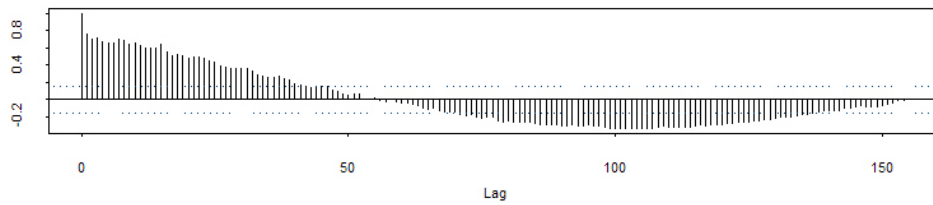


Series : AIHLL

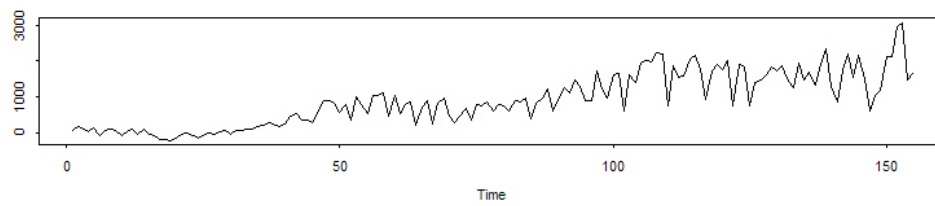
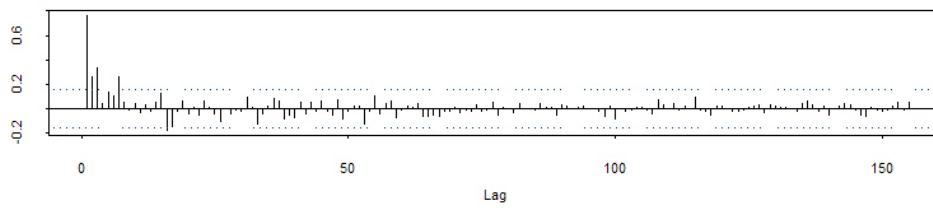




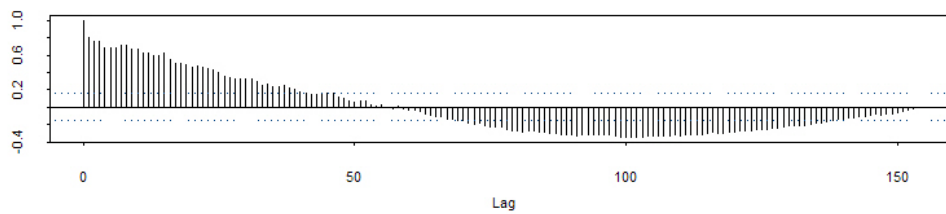
Series : AILHL



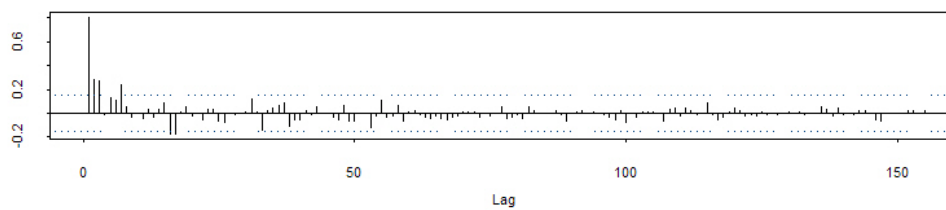
Series : AILHL

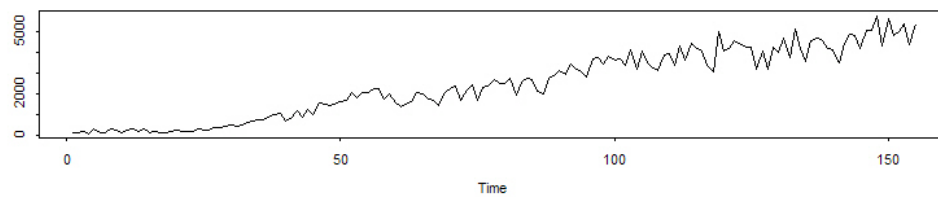


Series : AILLL

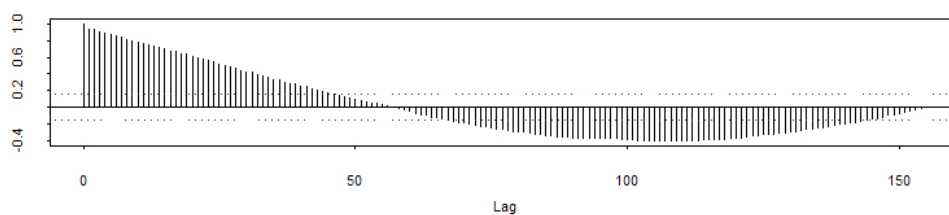


Series : AILLL

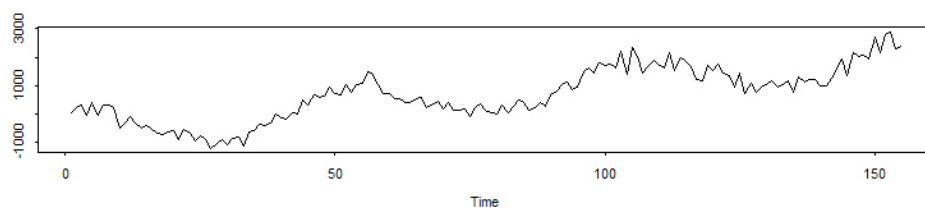
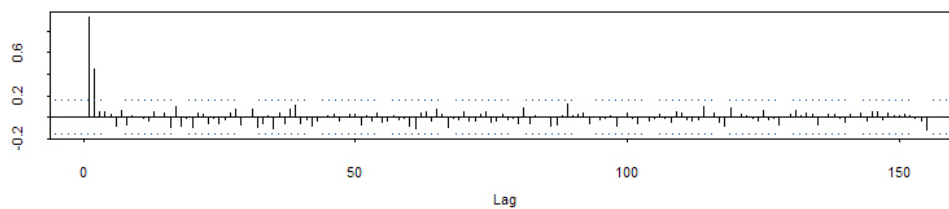




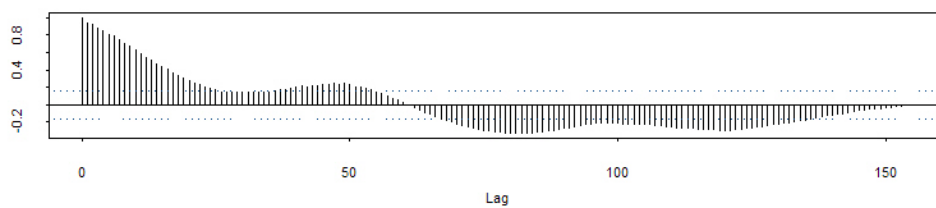
Series : AILMM



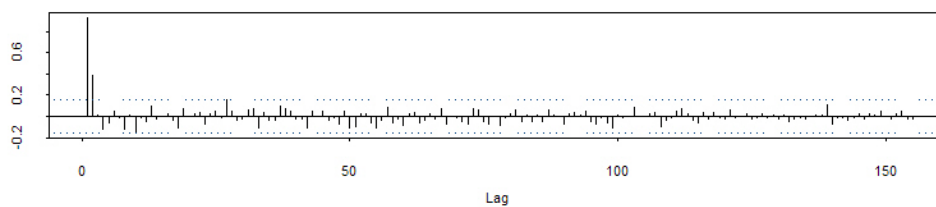
Series : AILMM

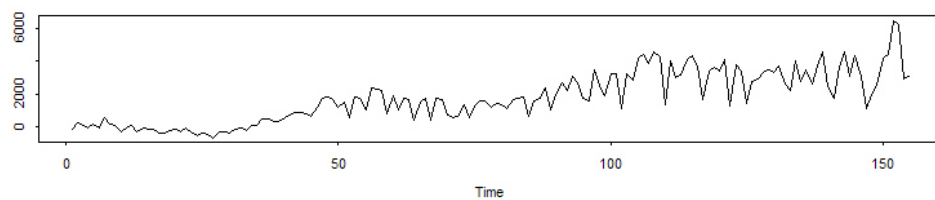


Series : AIMLM

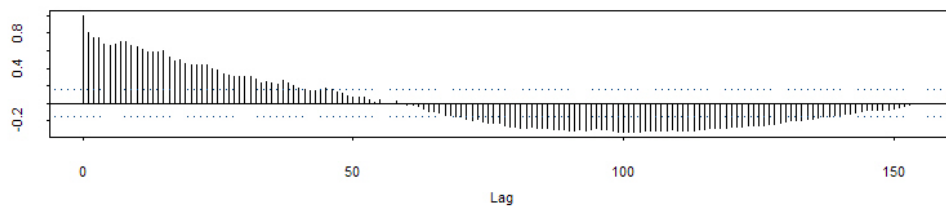


Series : AIMLM

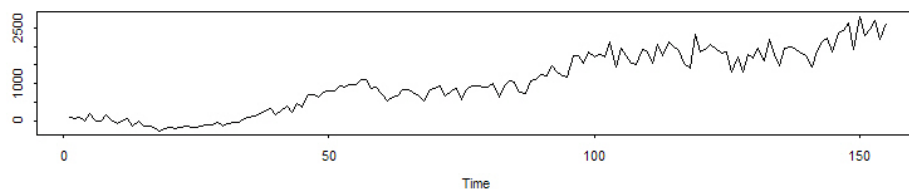
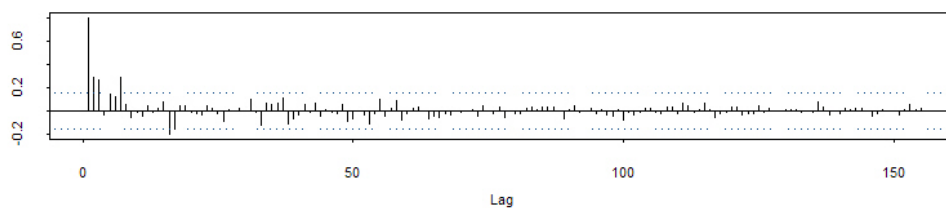




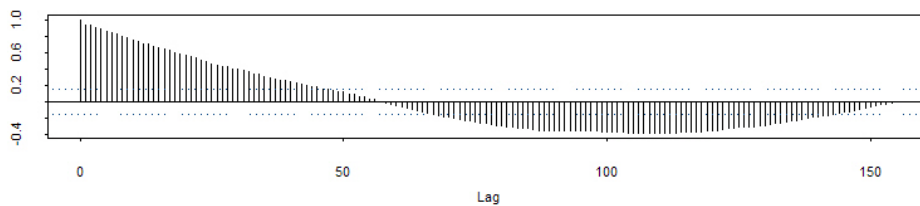
Series : AIMML



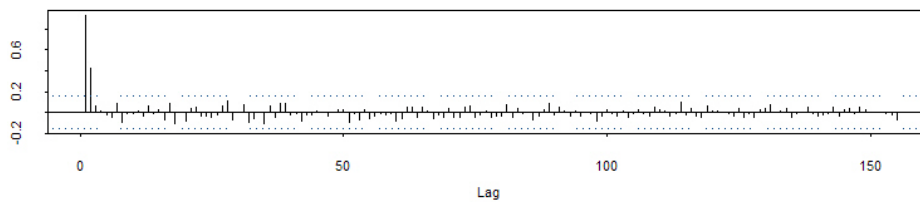
Series : AIMML

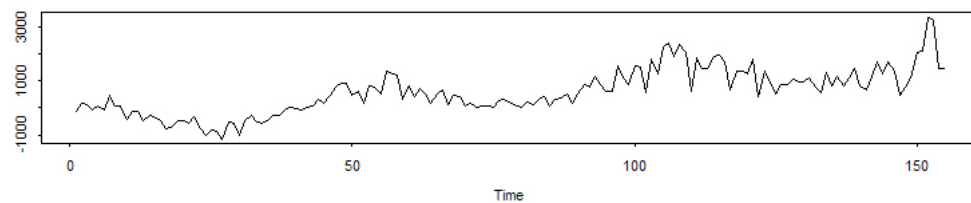


Series : AILLM

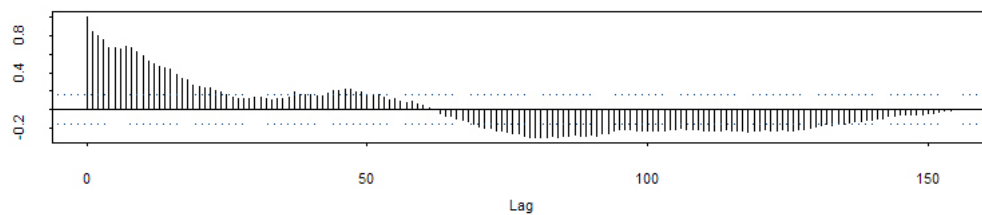


Series : AILLM

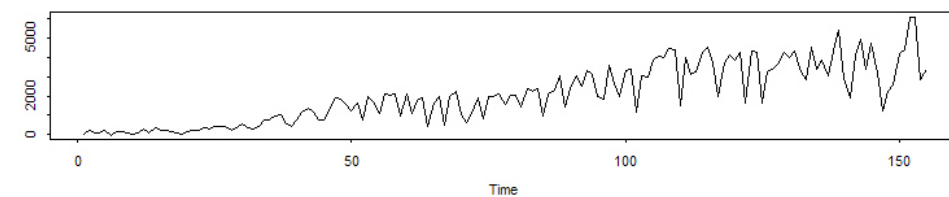
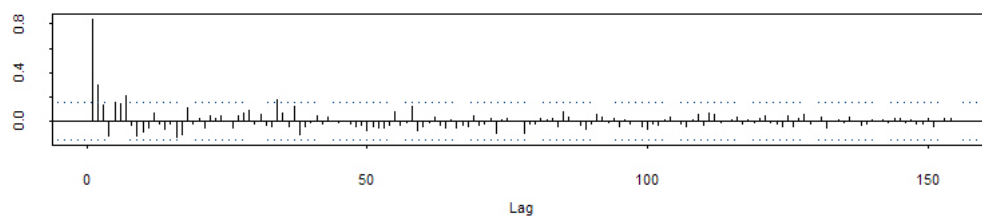




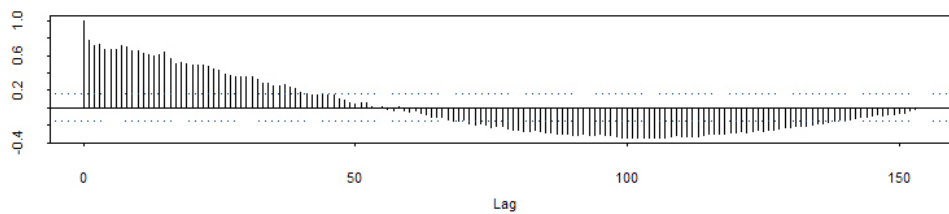
Series : AIMLL



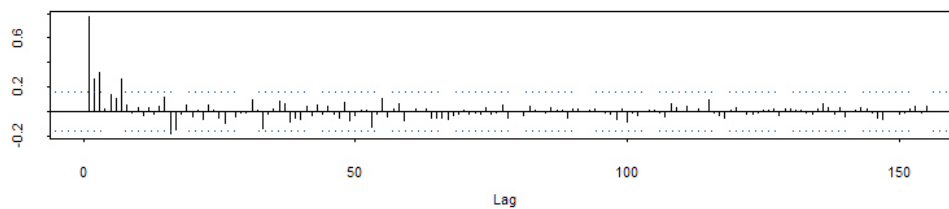
Series : AIMLL



Series : AILML



Series : AILML



APPENDIX B: TEST OF CORRELATION RESULTS

Correlation test of de-trended Refined Laspayres intensity index

```
#***** Refined Laspayres Intensity Index *****
cor.test(LIH HH, prodHw)
```

Pearson's product-moment correlation

```
data: LIH HH and prodHw
t = -0.7365, df = 153, p-value = 0.4625
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor  -0.05944053
```

```
> cor.test(LIM HH, prodHw)
```

Pearson's product-moment correlation

```
data: LIM HH and prodHw
t = -0.6679, df = 153, p-value = 0.5052
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor  -0.05391762
```

```
> cor.test(LIH MH, prodHw)
```

Pearson's product-moment correlation

```
data: LIH MH and prodHw
t = -0.6215, df = 153, p-value = 0.5352
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.05018343
```

```
> cor.test(LIH HM, prodMw)
```

Pearson's product-moment correlation

```
data: LIH HM and prodMw
t = -0.6405, df = 153, p-value = 0.5228
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.05171571
```



```

> cor.test(LIMMH, prodHw)

Pearson's product-moment correlation

data:  LIMMH and prodHw
t = -0.5507, df = 153, p-value = 0.5827
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.04447645

> cor.test(LIHMM, prodMw)

Pearson's product-moment correlation

data:  LIHMM and prodMw
t = -0.646, df = 153, p-value = 0.5192
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.05215641

> cor.test(LIMHM, prodMw)

Pearson's product-moment correlation

data:  LIMHM and prodMw
t = -0.6792, df = 153, p-value = 0.4981
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.05482426

> cor.test(LIMMM, prodMw)

Pearson's product-moment correlation

data:  LIMMM and prodMw
t = -0.6961, df = 153, p-value = 0.4874
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.056184

> cor.test(LILHH, prodHw)

Pearson's product-moment correlation

data:  LILHH and prodHw
t = -0.7278, df = 153, p-value = 0.4678
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.05874133

> cor.test(LIHLH, prodHw)

```

Pearson's product-moment correlation

```
data: LIHLH and prodHw
t = -0.4825, df = 153, p-value = 0.6302
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.03897485

> cor.test(LIHHL, prodLw)
```

Pearson's product-moment correlation

```
data: LIHHL and prodLw
t = 0.355, df = 153, p-value = 0.7231
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.02868749

> cor.test(LILHL, prodHw)
```

Pearson's product-moment correlation

```
data: LILLH and prodHw
t = -0.4753, df = 153, p-value = 0.6352
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.03839904

> cor.test(LIHLL, prodLw)
```

Pearson's product-moment correlation

```
data: LIHLL and prodLw
t = 0.092, df = 153, p-value = 0.9268
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.007435621

> cor.test(LILHL, prodLw)
```

Pearson's product-moment correlation

```
data: LILHL and prodLw
t = 0.3461, df = 153, p-value = 0.7297
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.02797184

> cor.test(LILLL, prodLw)
```

Pearson's product-moment correlation

```

data:  LILLL and prodLw
t = 0.0838, df = 153, p-value = 0.9334
alternative hypothesis:  coef is not equal to 0
sample estimates:

```

```

      cor
0.006771146

```

```
> cor.test(LILMM, prodMw)
```

```

Pearson's product-moment correlation

```

```

data:  LILMM and prodMw
t = -0.587, df = 153, p-value = 0.558
alternative hypothesis:  coef is not equal to 0
sample estimates:

```

```

      cor
-0.04740542

```

```
> cor.test(LIMLM, prodMw)
```

```

Pearson's product-moment correlation

```

```

data:  LIMLM and prodMw
t = -0.6759, df = 153, p-value = 0.5001
alternative hypothesis:  coef is not equal to 0
sample estimates:

```

```

      cor
-0.05456157

```

```
> cor.test(LIMML, prodLw)
```

```

Pearson's product-moment correlation

```

```

data:  LIMML and prodLw
t = 0.1901, df = 153, p-value = 0.8495
alternative hypothesis:  coef is not equal to 0
sample estimates:

```

```

      cor
0.01536753

```

```
> cor.test(LILLM, prodMw)
```

```

Pearson's product-moment correlation

```

```

data:  LILLM and prodMw
t = -0.5447, df = 153, p-value = 0.5868
alternative hypothesis:  coef is not equal to 0
sample estimates:

```

```

      cor
-0.04399379

```

```
> cor.test(LIMLL, prodLw)
```

```

Pearson's product-moment correlation

```

```

data:  LIMLL and prodLw
t = 0.0603, df = 153, p-value = 0.952

```

```
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.004878067
```

```
> cor.test(LILML, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LILML and prodLw
t = 0.2148, df = 153, p-value = 0.8302
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.01736321
```

```
> cor.test(LIHML, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LIHML and prodLw
t = 0.2234, df = 153, p-value = 0.8236
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.01805429
```

```
> cor.test(LIMHL, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LIMHL and prodLw
t = 0.3216, df = 153, p-value = 0.7482
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.0259903
```

```
> cor.test(LILMH, prodHw)
```

```
Pearson's product-moment correlation
```

```
data: LILMH and prodHw
t = -0.6135, df = 153, p-value = 0.5405
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
-0.04953381
```

```
> cor.test(LIHLM, prodMw)
```

```
Pearson's product-moment correlation
```

```
data: LIHLM and prodMw
t = -0.6149, df = 153, p-value = 0.5395
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```

      cor
-0.04965111

> cor.test(LIMLH, prodHw)

Pearson's product-moment correlation

data:  LIMLH and prodHw
t = -0.414, df = 153, p-value = 0.6795
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.03344878

> cor.test(LILHM, prodMw)

Pearson's product-moment correlation

data:  LILHM and prodMw
t = -0.5947, df = 153, p-value = 0.5529
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.04802122

```

Correlation test of de-trended Refined Laspayres intensity index

```
cor.test(LIHHH.mod, prodHw)
```

Pearson's product-moment correlation

```
data: LIHHH.mod and prodHw
t = -0.4992, df = 152, p-value = 0.6184
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.04045753
```

```
> cor.test(LIMHH.mod, prodHw)
```

Pearson's product-moment correlation

```
data: LIMHH.mod and prodHw
t = -0.5491, df = 152, p-value = 0.5837
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.04449444
```

```
> cor.test(LIHHM.mod, prodHw)
```

Pearson's product-moment correlation

```
data: LIHHM.mod and prodHw
t = -0.6107, df = 152, p-value = 0.5423
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.04947506
```

```
> cor.test(LIHHM.mod, prodMw)
```

Pearson's product-moment correlation

```
data: LIHHM.mod and prodMw
t = 0.6988, df = 152, p-value = 0.4858
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.05658693
```

```
> cor.test(LIMMH.mod, prodHw)
```

Pearson's product-moment correlation

```
data: LIMMH.mod and prodHw
t = -0.6539, df = 152, p-value = 0.5142
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.05296247
```

```

> cor.test(LIHMM.mod, prodMw)

Pearson's product-moment correlation

data:  LIHMM.mod and prodMw
t = 0.727, df = 152, p-value = 0.4683
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.05886591

> cor.test(LIMHM.mod, prodMw)

Pearson's product-moment correlation

data:  LIMHM.mod and prodMw
t = 0.6617, df = 152, p-value = 0.5091
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.05359633

> cor.test(LIMMM.mod, prodMw)

Pearson's product-moment correlation

data:  LIMMM.mod and prodMw
t = 0.6911, df = 152, p-value = 0.4905
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.05596997

> cor.test(LILHH.mod, prodHw)

Pearson's product-moment correlation

data:  LILHH.mod and prodHw
t = -0.4928, df = 152, p-value = 0.6229
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.03993842

> cor.test(LIHLH.mod, prodHw)

Pearson's product-moment correlation

data:  LIHLH.mod and prodHw
t = -0.7022, df = 152, p-value = 0.4836
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.05686178

> cor.test(LIHHL.mod, prodLw)

```

```

Pearson's product-moment correlation

data:  LIHHL.mod and prodLw
t = 0.7425, df = 152, p-value = 0.4589
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.06011677

> cor.test(LILLH.mod, prodHw)

```

```

Pearson's product-moment correlation

data:  LILLH.mod and prodHw
t = -0.6965, df = 152, p-value = 0.4872
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
-0.05640439

> cor.test(LIHLL.mod, prodLw)

```

```

Pearson's product-moment correlation

data:  LIHLL.mod and prodLw
t = 0.7425, df = 152, p-value = 0.4589
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.06011677

> cor.test(LILHL.mod, prodLw)

```

```

Pearson's product-moment correlation

data:  LILHL.mod and prodLw
t = 0.75, df = 152, p-value = 0.4544
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.06072259

> cor.test(LILLL.mod, prodLw)

```

```

Pearson's product-moment correlation

data:  LILLL.mod and prodLw
t = 0.8833, df = 152, p-value = 0.3785
alternative hypothesis:  coef is not equal to 0
sample estimates:
      cor
0.07146103

> cor.test(LILMM.mod, prodMw)

```

```

Pearson's product-moment correlation

```



```
data: LILMM.mod and prodMw
t = 0.7113, df = 152, p-value = 0.478
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.05760082
```

```
> cor.test(LIMLM.mod, prodMw)
```

```
Pearson's product-moment correlation
```

```
data: LIMLM.mod and prodMw
t = 0.7175, df = 152, p-value = 0.4742
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.05809506
```

```
> cor.test(LIMML.mod, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LIMML.mod and prodLw
t = 0.8446, df = 152, p-value = 0.3996
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.06834972
```

```
> cor.test(LILLM.mod, prodMw)
```

```
Pearson's product-moment correlation
```

```
data: LILLM.mod and prodMw
t = 0.7338, df = 152, p-value = 0.4642
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.0594142
```

```
> cor.test(LIMLL.mod, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LIMLL.mod and prodLw
t = 0.9024, df = 152, p-value = 0.3683
alternative hypothesis: coef is not equal to 0
sample estimates:
```

```
cor
0.07299632
```

```
> cor.test(LILML.mod, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LILML.mod and prodLw
```

```
t = 0.824, df = 152, p-value = 0.4113
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.06668282
```

```
> cor.test(LIHML.mod, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LIHML.mod and prodLw
t = 0.8162, df = 152, p-value = 0.4157
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.06605504
```

```
> cor.test(LIMHL.mod, prodLw)
```

```
Pearson's product-moment correlation
```

```
data: LIMHL.mod and prodLw
t = 0.7727, df = 152, p-value = 0.4409
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.06255038
```

```
> cor.test(LILMH.mod, prodHw)
```

```
Pearson's product-moment correlation
```

```
data: LILMH.mod and prodHw
t = -0.6047, df = 152, p-value = 0.5463
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
-0.04899197
```

```
> cor.test(LIHLM.mod, prodMw)
```

```
Pearson's product-moment correlation
```

```
data: LIHLM.mod and prodMw
t = 0.7522, df = 152, p-value = 0.4531
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.06089597
```

```
> cor.test(LIMLH.mod, prodHw)
```

```
Pearson's product-moment correlation
```

```
data: LIMLH.mod and prodHw
t = -0.7396, df = 152, p-value = 0.4607
alternative hypothesis: coef is not equal to 0
```

```

sample estimates:
      cor
-0.05987879

> cor.test(LILHM.mod, prodMw)

Pearson's product-moment correlation

data:  LILHM.mod and prodMw
t = 0.6864, df = 152, p-value = 0.4935
alternative hypothesis: coef is not equal to 0
sample estimates:
      cor
0.05558499

```

VITA

Wisit Kumphai

Candidate for the degree of

Doctor of Philosophy

Thesis: ENERGY INDEX DECOMPOSITION METHODOLOGY AT THE PLANT
LEVEL

Major Field: Industrial Engineering and Management

Biographical:

Education: Graduated from Kasetsart University Laboratory School in Bangkok, Thailand in March, 1994; received Bachelor of Engineering in Mechanical Engineering from Kasetsart University, Bangkok, Thailand; received Master of Science degree in Industrial and Systems Engineering from Colorado State University – Pueblo. Completed the requirements for the Doctor of Philosophy degree with a major in Industrial Engineering and management at Oklahoma State University in December 2006.

Experience: Employed by Oklahoma Industrial Assessment Center, Oklahoma State University as a research assistant from 2000 to 2006. Employed by Sieben Energy Associates in Chicago, Illinois as a senior energy engineer from 2006 to present.

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Title of Study: ENERGY INDEX DECOMPOSITION METHODOLOGY AT
THE PLANT LEVEL

Pages in Study: 116

Candidate for the Degree of Doctor of Philosophy

Major Field: Industrial Engineering and Management

Scope and Method of Study: The dissertation explores the use of a high level energy intensity index as a facility-level energy performance monitoring indicator with a goal of developing a methodology for an economically based energy performance monitoring system that incorporates production information. The performance measure closely monitors energy usage, production quantity, and product mix and determines the production efficiency as a part of an ongoing process that would enable facility managers to keep track of and, in the future, be able to predict when to perform a recommissioning process. The study focuses on the use of the index decomposition methodology and explored several high level (industry, sector, and country levels) energy utilization indexes, namely, Additive Log Mean Divisia, Multiplicative Log Mean Divisia, and Additive Refined Laspeyres. One level of index decomposition is performed. The indexes are decomposed into Intensity and Product mix effects. These indexes are tested on a flow shop brick manufacturing plant model in three different climates in the United States. The indexes obtained are analyzed by fitting an ARIMA model and testing for dependency between the two decomposed indexes.

Findings and Conclusions: The results concluded that the Additive Refined Laspeyres index decomposition methodology is suitable to use on a flow shop, non air conditioned production environment as an energy performance monitoring indicator. It is likely that this research can be further expanded in to predicting when to perform a recommissioning process.

ADVISER'S APPROVAL: David B. Pratt
